Consumer rationality in choice

Conlon, B.J.

Publication date:
2001

Document Version
Publisher's PDF, also known as Version of record

Link to publication in Tilburg University Research Portal

Citation for published version (APA):
Conlon, B. J. (2001). *Consumer rationality in choice*. [Doctoral Thesis, Tilburg University]. CentER, Center for Economic Research.

CentER

Consumer Rationality in Choice

Bernard Conlon

Consumer Rationality in Choice

Consumer Rationality in Choice

PROEFSCHRIFT

ter verkrijging van de graad van doctor aan de Katholieke Universiteit Brabant, op gezag van de rector magnificus, Prof. dr. F. A. van der Duyn Schouten, in het openbaar te verdedigen ten overstaan van een door het college voor promoties aangewezen commissie in de aula van de Universiteit op

vrijdag 29 juni 2001 om 14.15 uur

door

BERNARD JOHN CONLON

geboren op 28 oktober 1972 te Sydney Australië

PROMOTOR: Prof. dr. A. H. O. van Soest

COPROMOTOR: Dr. ir. B. G. C. Dellaert

for my wonderful son

Maximo

Acknowledgments

This thesis represents the culmination of four and a half years work carried out at the CentER for Economic Research at Tilburg University in The Netherlands. I would like to thank CentER for providing me this opportunity and in addition to CentER*data* for providing the surveys upon which the work is based.

I would like to thank all of the academic staff who have helped me by either conducting courses that I followed, or for playing a role in the completion of this thesis. Many thanks also go to the administrative staff of the 8^{th} floor who helped me to settle into my new life in The Netherlands in so many ways. From 'giros' to bike shops they were always willing to help in whichever way they could.

The thesis committee consisting of Arthur van Soest, Benedict Dellaert, Rik Pieters, Harry Timmermans, Bob Bartels, and Denzil Fiebig also deserve a special mention, particularly the last two whom, in addition to toiling over the thesis, travelled half way around the world to be present at my defence.

Most of all I'd like to thank all of the friends I have met over my time in Tilburg especially fellow PhD students for making me feel less insane. Special mentions go to: The Dutchies, The Russians, The Slovaks, The Italians, The Poles, Bas, Xia Dong, and all friends outside of the Uni, especially Willem, Martin, Ekin, and Klaas.

Exceptional mentions go to:

Arthur and Benedict - for not letting me quit and being my guide,
Mum, Dad and family - for listening whenever I cried,
Pia and Maximo - for the time spent by my side,
And last of all my conscious self for the rollercoaster ride.

Long live the eighth floor, my home away from home!

Bernard Conlon
February 2001

Contents

Chapter 1

Introduction

The issue of modelling consumer preferences and the choice processes they use is fundamental to the marketing profession. Understanding consumer choice behaviour can lead to significant changes in product or service design, pricing strategy, distribution channel and communication strategy selection, as well as public welfare analysis (Louviere et al., 2000). The most common method currently used for eliciting consumer preferences is the estimation of multi-attribute choice models. Multi-attribute choice models have evolved into a major research area in the marketing literature. The ability of these models to predict future choice distributions and to provide diagnostic information which enables the researcher to better understand the behavioural process underlying the choices makes attribute choice models a topic of interest, not only for marketing, but to a wide range of disciplines. These include psychology, economics, management and transportation.

Multi-attribute choice models come with diverse structural forms, purposes, and underlying assumptions. Most of the current models assume a perfectly rational utility-maximising decision-maker who determines the utility value of a product by evaluating all of the attributes associated with it simultaneously, weighing the relative worth of each attribute in a compensatory manner. However, there is a lot of evidence to suggest that consumers frequently do not fit into this idealised framework. The aim of this thesis is to enhance our understanding of the way people choose and explain any deviations from the behaviour predicted by utility maximising models of choice. More specifically, models that allow and test for behaviour characterised by bounded rationality rather than full rationality are introduced and empirical evidence supporting these models is provided. The empirical work in this thesis is based upon two major surveys, conducted by CentER*data*, and specifically designed for the purpose of analysing consumer choice behaviour. To analyse these extensive data sets modern econometric techniques are employed, refining existing methods.

In the next section of this introductory chapter we expand on the motivation leading to this research. The second section describes the four individual research topics in more detail and discusses the specific contribution each of them provides.

1.1 Motivation

Suppose we are concerned with modelling a consumer who is faced with the problem of choosing a single element from a set of multidimensional items, the dimensions representing attributes of the items. Traditional economic theory would presuppose the decision-maker knew his or her preferences, could observe all attributes of all items without costs, and could effortlessly select the alternative that maximises the decision-maker's "utility function" defined over the attributes of the item. An economic agent possessing these abilities is referred to in the economics literature as "perfectly rational". Researchers have often been apologetic about the assumption that decision-makers are perfectly rational and prefer to take this assumption less literally. That such a perfectly rational model is inadequate, as a representation of practical consumer behaviour, has long been recognised (Simon 1955). Numerous empirical studies have provided evidence of systematic violations of the perfectly rational man paradigm (e.g., Tversky and Kahneman 1986, Schoemaker 1982).

This dissatisfaction with models that adhere to the perfectly rational man assumptions, has motivated the development of models assuming a more realistic alternative: the boundedly rational decision-maker. It is with this individual that this thesis is mainly concerned. Most models of bounded rationality are based, at least implicitly, on the notions that information is costly and that the human capacity for processing information is neither unlimited nor effortless. So when faced with complex or unfamiliar choices individuals frequently appear to employ simpler decision rules, which have lower requirements for information processing than the fully compensatory utility maximising decision strategy. Our perception of the boundedly rational individual differs depending on the underlying beliefs as to why we observe that agents use simplifying strategies. Some researchers propose theories of strategy selection that are based on the idea that complex decision environments result in a gap between the competence or cognitive ability of the decision-maker and the difficulty of the decision. This suggests that the simpler alternatives are employed because individuals sometimes cannot carry the fully compensatory utility maximising strategy. Another perspective suggests that a boundedly rational decision-maker looks at strategy selection as a function of both costs, primarily the effort required to use a rule, and benefits, primarily the ability of a strategy to select the best alternative. A cost-benefit approach to strategy selection maintains the concept of calculated rationality by including costs of executing the decision process in the assessment of rationality. Therefore deviations from the behaviour predicted for a perfectly rational utility maximising individual may be logically explained as the result of optimising behaviour.

Whether boundedly rational behaviour can be explained as utility optimisation when cognitive costs are incorporated into the utility function, or as resulting from a cognitive gap, the implication is that decision complexity should play a role in determining the choice process. Increased complexity should in general lead to a greater tendency to simplify choice problems. Under the assumption that decision-makers are perfectly rational this is not the case, but rather complete processing of all information is always carried out.

Another observation suggesting individuals are not perfectly rational is the existence of framing effects. A framing effect occurs when different behaviour is observed due to changes in the way a decision is framed, not in the content of the choice problem. That is, under different task conditions, consumers exhibit different preferences. Other examples of this kind of task effect are the differences between preferences estimated from revealed preference and stated preference data, or the different preferences being elicited from choice data, or ratings data. A ratings questionnaire differs from choice questions in that rather than providing individuals with sets of goods and asking them to indicate a preferred option, people are shown only one option, and asked to rate its value on some given scale.

To analyse these different forms of bounded rationality and gain insight into consumer choice behaviour it is often useful to collect information other than standard choice data and to model the information contained in the various data types jointly (Hensher Louviere and Swait 1999). A secondary theme of the thesis is therefore the provision of econometric methods for combining various data types. The more extensive models that result are useful not only for comparing estimated consumer preferences across various task conditions, but also for examining the types of decision strategies individuals are using and the determinants of strategy selection.

1.2 Overview

The following four chapters of the thesis are comprised of four self-contained yet closely related pieces of research examining consumer choice behaviour and providing evidence for, or incorporating elements of, boundedly rational behaviour. The empirical work in these chapters is based upon two major surveys sent out to members of the CentER*data* consumer panel, consisting of a cross-section of households throughout The Netherlands. The panel is administered through Tilburg University for the purpose of economic research. Both surveys were designed using conjoint methods specifically for the current research. The next two chapters use the first survey and concentrate on providing evidence of boundedly rational behaviour. Chapters 4 and 5 employ the second survey and examine reasons why simplifying strategies might be used. A theoretical model, which includes cognitive costs in the decision-makers utility function, finds that the fully compensatory choice process is no longer optimal in chapter 4. An explicit model for one alternative to the fully compensatory strategy is suggested in chapter 5. A brief description of each chapter is now given.

Chapter 2: Complexity and Accuracy in Consumer Choice

In chapter two we begin by analysing the possibility that an individual's choice process may be affected by the complexity of the choice environment. As explained in section 1.1, the assumption of perfect rationality implies that the decision-maker has the skill necessary to make whatever complicated calculations are needed to discover his optimal course of action, and can do so costlessly. Under these conditions choice set complexity should play no role in the choice process. However, under the alternative assumption of boundedly rational agents, we may expect higher levels of complexity to be associated with less accurate decisions.

To analyse the relationship between choice complexity and choice accuracy we use conjoint data on consumer yoghurt choice in The Netherlands for a large sample of consumers. A mixed logit model is estimated via simulated maximum likelihood where random coefficients capture unobserved heterogeneity, while remaining error terms, assumed to be independent over questions, are interpreted as choice errors. The variance of these error terms is allowed to be question specific, to allow for an effect of choice set complexity on the size of the error. Two new measures of choice accuracy are defined and computed on the basis of these mixed logit estimates.

The paper also suggests measures for the complexity of a given choice situation that make use of the mixed logit parameter estimates, following the seminal work of Shugan (1980). The accuracy measures are regressed on the variables measuring choice complexity. The accuracy is found to be significantly affected by context based complexity measures such as attribute variability, within alternative attribute covariance, and the utility difference between products. The directions of these effects are in line with the predictions from the literature. The paper thus provides clear evidence of complexity effects in choice indicating that decision-makers would be better described by a boundedly rational framework than by a perfectly rational model.

Chapter 3: Combining and Comparing Consumers' Stated Preference Ratings and Choice Responses

The second essay considers the question of how to combine two different types of data sources for the same individuals, with the aim to estimate the same set of consumer preferences. The survey upon which the empirical example is based is the same as is used for chapter 2, however now, in addition to the choice data, preference ratings data for the same individuals are also incorporated in the model. As the same consumers are analysed using both types of preference data, the preference estimates elicited using either data source should be compatible. On the other hand, evidence of framing effects in economic decision-making is well established (Tversky and Kahneman 1986) suggesting different task conditions may affect an individual's preferences. In a similar manner we may expect task effects due to the difference in task conditions between the ratings and choice questions.

To examine whether differences exist between the way individuals respond to different preference elicitation procedures it is useful to analyse the data sets in a joint model. For this purpose an econometric model for combining choice and preference ratings data collected from the same set of individuals is developed and tested. Choice data are modelled using a multinomial logit framework, while preference data are modelled using an ordered response equation. A flexible monotonic transformation from utility to ratings is allowed for by making the category bounds in the ordered probit free parameters to be estimated. Individual heterogeneity is allowed for via random coefficients providing a link between the choice and ratings data. Estimation and identification issues are discussed as well as potential efficiency gains over models considering the two data sets separately.

Applying the model to the survey data, we find that ratings based preference estimates differ significantly from choice based estimates suggesting task effects are occurring. While the mean parameters for the preference distributions differ, the correlation between the random coefficients driving the two data sets is very strong. This gives the model an advantage over separate models explaining choice or ratings, and helps to improve predictions.

Chapter 4: Optimal Effort in Consumer Choice

The focus of Chapter 4 is the development of a model for a boundedly rational consumer who, while not satisfying the strict requirements of the perfect rationality assumption, is still assumed to exhibit calculated rationality. The model considers an individual who attaches a cost to the effort involved with cognitive processing, and when deciding on which decision strategy to use, includes the cost of executing the decision process in the utility function. This cost-benefit perspective provides potential for explaining why decision strategies vary across situations.

Based on the framework of a cost-benefit trade-off a theoretical model of optimal effort in consumer choice is developed. The model extends previous consumer choice models in that the consumer not only chooses a product but first decides how much effort to apply to a given choice problem. Rather than considering only the payoff of the chosen outcome, the consumer's objective function also contains the costs of cognitive effort.

The optimal level of effort in any given choice situation is based on the consumer's cost of effort, the expected utility gain of a correct choice and the complexity of the choice set. To explore the empirical validity of the model a second survey was conducted by CentER*data* on their consumer panel in The Netherlands. The subject of the survey was consumer restaurant choice. Response time was measured as a proxy for effort, while consumer involvement measures were taken as proxies for individual differences in cost of effort and perceived complexity. The response time for each choice question was explained by the respondent specific consumer involvement measures, and from two choice task specific variables: the (estimated) utility difference between alternatives, and the number of elementary information processes (EIP's).

The findings were consistent with the theoretical model suggesting that consumers indeed do consider mental effort as being costly and adapt their choice processes accordingly. Individual differences as explained by consumer involvement also supported this result. For example, response time was found to increase with the consumer's interest and pleasure, which is in line with the notion that for very interested consumers, the cost of effort (compared to the expected utility gain of a correct choice) will be low. Effort was found to increase with both the utility difference and the task complexity.

Chapter 5: Effort, Decision Strategy and Choice: How many attributes do consumers consider?

In Chapter 5 we propose and implement a new model for the choice process of a boundedly rational individual as an alternative to the fully compensatory model. The model allows for the possibility that consumers may simplify the decision task by not considering all of the attribute information provided for alternatives. There has been considerable evidence in the literature on consumer choice to suggest that consumers frequently do not follow the fully compensatory choice process preferring instead to employ simpler decision rules. The basic premise underlying the model therefore is that consumers may base their choices on subsets of the attributes rather than all the attributes. This seems particularly relevant for choice situations with few alternatives characterised by many attributes.

The model takes the mixed multinomial logit model as a starting point, but it incorporates the possibility that individuals base their choice on a limited number of product attributes only. To allow for heterogeneity across individuals the attribute weights or preferences are allowed to vary across the population of consumers. The decision-maker is assumed to have a threshold value that determines which attributes are important enough to be considered in any given choice situation. If the difference between the utility contributions of a given attribute across the products in the choice situation is below the threshold, the attribute is not taken into account in the choice. The specification allows for systematic and random heterogeneity in the threshold levels so that different decision-makers may vary in the extensiveness of the decision process. We allow the threshold to vary systematically with both response time and complexity. We find that higher response times (or higher effort) are associated with lower thresholds. This makes sense as a lower threshold leads to consideration of more attributes. We also find individuals that increase the number of attributes they consider (lower their thresholds) as choice complexity increases. With inclusion of the individual-specific attribute weights and thresholds, different decision-makers are then allowed to vary both in terms of which and how many attributes they consider, incorporating a broad range of decision strategies.

The model is implemented on the same data set as was seen in Chapter 4, however, additional attribute-specific information is now also incorporated. This supplementary data includes information on which attributes were always used, which were never used, and an importance rating for the attributes seen by each respondent. The inclusion of the additional information helps to disentangle the various individual choice processes which enables us to identify the model. A smooth simulated maximum likelihood procedure is introduced to obtain estimates of the model parameters. The estimation results and, in particular, the structural link between preference weights and whether or not attributes are considered in the choice decisions, are illustrated by comparing posterior distributions of the random coefficients given information on which attributes are and are not considered. This is similar to a recently developed method for obtaining the distributions of individual parameters conditional on their observed choices developed by Revelt and Train (1999).

The main results of the thesis are summarized in Chapter 6 and some general conclusions are provided. Suggestions for future research in the area of boundedly rational consumer choice are also given.

Chapter 2

Complexity and Accuracy in Consumer Choice

In this chapter we analyse the relationship between choice complexity and choice accuracy using conjoint choice data from a large sample of consumers. We estimate a mixed logit framework where random coefficients capture unobserved heterogeneity, while remaining error terms, assumed to be independent over questions, are interpreted as choice errors. The variance of these error terms is allowed to be question specific, to allow for an effect of choice set complexity on the size of the error. The mixed logit estimates are used to compute two measures of choice accuracy for the average respondent for each question. They are also used to define various measures of choice complexity for each question. We then regress the accuracy measures on the complexity measures. We find that accuracy is significantly affected by the context based complexity measures: attribute variability, within alternative attribute covariance, and utility difference between alternatives. The signs of these effects are in line with the predictions in the literature. On the other hand, we do not find a significant effect of task complexity on choice accuracy.

2.1 Introduction

How consumers respond to possible changes in product characteristics and price is one of the central questions in marketing and the past success of consumer choice modelling is due largely to its ability to predict such consumer responses. Most research on consumer choice modelling has focused on consumers' structural responses, i.e., each consumer's average response to changes in product features. Recently, however, researchers also have begun to investigate the impact and size of errors in consumers' preferences and choices. For example, de Palma et al. (1994), analysed economic implications of consumers' imperfect ability to choose, Dellaert et al. (1999) explored the effect of attribute variation on consumer choice consistency, Fischer et al. (2000) investigated the impact of within alternative attribute conflict on judgement time and error, and Haaijer et al. (2000) tested a choice model specification that takes into account differences in choice response error between individuals.

Previous research has led to two important conclusions. First, the accuracy with which consumers express their preferences and choices is not stable across contexts and tasks (Fischer et al. 2000, Haaijer et al. 2000). Second, the implications of such variations for consumer welfare and producer marketing effectiveness can be considerable (de Palma et al. 1994). A strong empirical finding with respect to variations in accuracy in consumer judgement and choice is that such variations can be caused by changes in choice set complexity (Dellaert et al. 1999, Fischer et al. 2000).

The premise that choice complexity may affect the accuracy of choice outcomes is not new. For example, Johnson and Payne (1985) showed that the accuracy of different choice rules depends on the complexity of the choice task. Bettman et al. (1990) examined the cognitive processing requirements associated with various decision rules and suggested that individuals may switch to simpler, less accurate choice rules as choice task complexity increases. However, only recently have researchers begun to incorporate variations in error in models of consumer choice. In particular, random utility theory offers a conceptual framework for modelling variations in consumer choice accuracy, because it introduces a random error component in the consumer utility function that can capture unexplained variations in consumer choice behaviour. Recent studies in marketing and economics have acknowledged the role of random error variations in modelling consumer choice and have allowed for differences in unexplained variance in consumer utility functions. This has led to the development and implementation of such models as the heteroskedastic logit model (Allenby and Ginter 1995) and parameterised versions of the heteroskedastic multinomial logit models (Dellaert et al. 1999, Haaijer et al. 2000). Still, in this stream of research relatively little effort has been directed at finding a behavioural basis for observed differences in consumer choice accuracy.

In this study we investigate the impact of various psychological aspects of complexity on choice accuracy in a formal model of accuracy and complexity. We distinguish between task and context based aspects of complexity. We measure task based complexity by the combined effect of the number of attributes and the number of alternatives in the choice set (Johnson and Payne 1985). Context based complexity is measured by the variability of attribute utilities (Shugan 1980, Fischer et al. 2000), the covariance between attribute utilities (Shugan 1980, Johnson and Payne 1985) and the difference in total utility between alternatives (Shugan 1980). In line with previous heteroskedastic logit modelling approaches, we allow for a flexible specification of the error variance across different choice sets. Furthermore, we add to this approach a mixed logit specification (McFadden and Train 2000) that allows for variation in responses across individuals due to variation in preferences.

In contrast to previous approaches (Dellaert et al. 1999, Haaijer et al. 2000), we do not use the logit model estimates directly to model complexity effects, but rather use the estimates as input for a regression model explaining specifically formulated choice accuracy measures from the proposed choice complexity measures. The observations in this regression model are based on all the different questions in the survey. The dependent and independent variables are the accuracy measures and the task and context based complexity measures for the average consumer respectively. Both the dependent and the independent variables are constructed on the basis of the mixed logit results. This two-stage approach allows us to investigate the relationship between choice complexity and choice accuracy more adequately because the measures of accuracy are based on consumers' performance relative to optimal and random behaviour. Therefore these measures can be generalised over choice sets of different composition, something which is not possible for the error variance measure used by Dellaert et al. (1999) and Haaijer et al. (2000).

Empirically, we investigate the impact of complexity on consumer choice accuracy using consumer choices in experimentally manipulated choice sets with different levels of complexity. Our main conclusion from this empirical investigation is that variations in choice accuracy are driven by variations in the three context effects but not by variations in task effects. We observe shifts in accuracy similar in nature to those observed for consumer judgements by Fischer et al. (2000) and those suggested by Shugan (1980). This finding suggests that consumers increase their effort in response to shifts in task effects, possibly because they base their choice effort on task variables (number of alternatives and attributes). On the other hand, they do not adjust their effort to changes in context variables enough to keep accuracy constant. This finding is also in line with Johnson and Payne's (1985) observation that the effort involved in following a certain choice strategy depends on task variables only, while for given effort, the level of accuracy is driven by context effects.

In the remainder of this chapter we first discuss the theoretical and modelling basis for our study (section 2.2). Section 2.3 covers our empirical study, describing the experimental choice data, the estimates and their implications. In section 2.4, we present some conclusions, a discussion, and suggestions for future research.

2.2 Theory and Model

Our discussion of the various aspects of the theory and the model is structured in four subsections. First, we discuss the random coefficients heteroskedastic mixed logit model that provides the estimates of preferences and error term variances, which are the basis for constructing choice set complexity and choice accuracy measures (subsection 2.2.1). Secondly, we develop the measures to describe choice set complexity (subsection 2.2.2). These measures are based on previous research in psychology and marketing. Thirdly, two choice accuracy measures are defined (subsection 2.2.3). Both the choice complexity and the choice accuracy measures use the estimates from the consumer choice model as input. Fourthly, the model describing the relationship between choice set complexity and consumer choice accuracy is discussed, together with the hypotheses that we want to test empirically (subsection 2.2.4). The structure as a whole, how it is discussed in the following sections and how the underlying choice model is put to use, is presented graphically in figure 2.1.

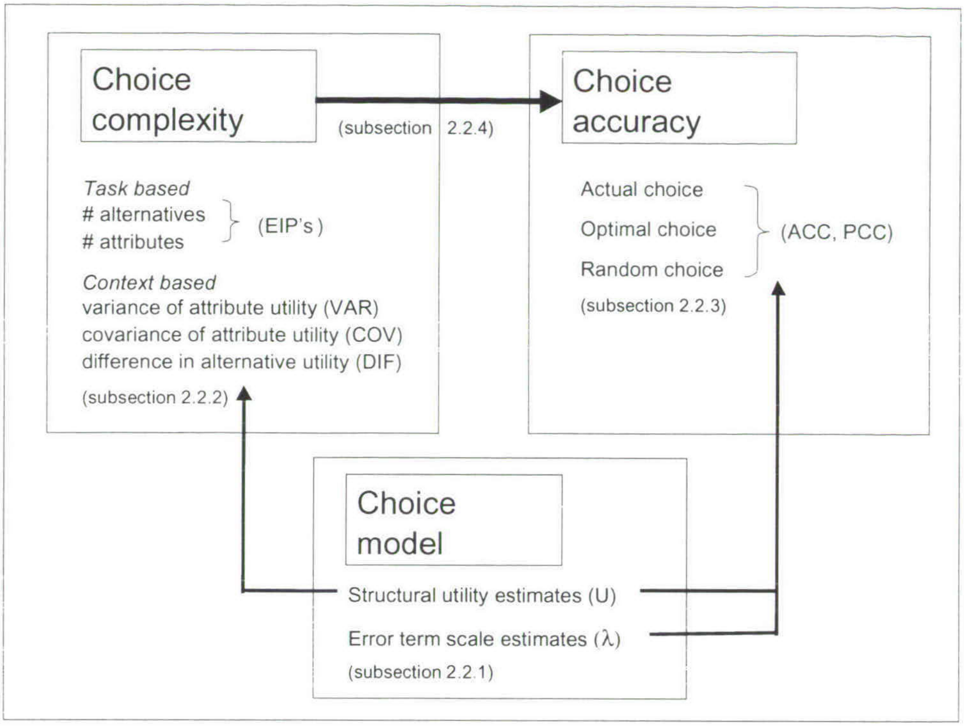

Figure 2.1: Model Structure

2.2.1 A Random Coefficients Heteroskedastic Logit Model Of Consumer Choice

The model used to analyse the consumers' choice data and to obtain the preference parameters required for the analysis of the relation between accuracy and complexity is based on the well-known multinomial logit model. To accommodate heterogeneity across respondents, we allow for random variation in the attribute coefficients, and use a random coefficients specification. We use the following notation:

i	respondent (i=1,...,N), N is the total number of respondents
s	choice situation (s=1,...,S), S is the total number of choice situations
k	attribute (k=1,...,K), K is the total number of attributes considered in all choice situations.

j alternative ($j=0,1,\ldots,J(s)$), $J(s)$ is the number of alternatives in choice set s

$X_j = (x_{j1},\ldots,x_{jK})'$ vector of attribute values of alternative j, X_j does not include a constant.

Attribute values of attributes that are not considered (in a given choice situation), are set to zero (by normalisation).

Let the utility of alternative j to respondent i be given by:

(2.1) $$U_{ij} = X_j'\beta_i \qquad j=1,\ldots,J(s)$$

The vector of slope coefficients $\beta_i=(\beta_{i1},\ldots,\beta_{iK})'$ may vary across respondents. This will reflect heterogeneity in preferences, i.e., in the marginal utilities of the attributes (see (2.3) below). McFadden and Train (2000) show that, if the distribution of β_i is flexible enough, the mixed logit specification can be used to approximate the choice probabilities of a large class of discrete choice models based on random utility maximisation.

The consumer choices to be modelled all contain the option of not choosing any of the products offered, referred to as the 'none'-option. Let alternative j=0 be this 'none'-option, and let its utility to respondent i be given by:

(2.2) $$U_{i0} = \beta_{i0}$$

The 'none'-option differs from the other alternatives in that it does not have any attribute values[1].

The β_{i0} and β_i are treated as random coefficients, using the following specification:

(2.3) $$\beta_{ik} = b_k + u_{ik}, \quad k=0,\ldots,K,$$

(2.4) $$u_i = (u_{i0},u_{i1},\ldots,u_{iK}) \sim N(0,\Omega)$$

The unobserved characteristics of the respondent enter via u_{ik}. It is assumed that the u_{ik} are drawn from a multivariate normal distribution with mean zero. Note that β_i is respondent specific but not choice situation or alternative specific; respondent i's choices are all assumed to be based on the same β_i. The parameters in the $(K+1)\times(K+1)$ matrix, Ω, are to be estimated. For computational convenience, it is assumed that Ω is diagonal, so that only $(K+1)$ standard deviations ω_k need to be estimated. The random coefficients β_{i0} and β_i (or the

[1] Equivalently, the utility of the 'none'-option could be normalised to 0, and a respondent specific base level utility (not varying over choice sets or alternatives) could be added to the utility values of the other alternatives.

u_{ik}) vary neither with choice situations, nor with alternatives, and are independent across individuals. As a consequence, the variances of the random coefficients are identified by the correlation structure of the choices across choice situations and alternatives. Similar to Fischer et al. (2000), we interpret the differences in error not only in terms of model fit differences between choice tasks but also in terms of differences in response error ('preference uncertainty'). We allow the error to vary between choice tasks of different composition because we are interested in the question whether responding to some choice tasks may be more difficult than responding to others.

In constructing a choice probability model, we follow the usual random utility framework. Choices are based upon the sum of 'true' utilities U_{ij} and error:

(2.5) $$U_{ijs}^* = U_{ij} + \varepsilon_{ijs} \qquad j=0,\ldots,J(s),\ s=1,\ldots,S.$$

Respondent i chooses alternative c in choice situation s if and only if $U_{ics}^* \geq U_{ijs}^*$ for all alternatives j in that choice situation.

There are two unobserved random variables in this model, with quite different interpretations. The u_i reflect unobserved heterogeneity across respondents; they are respondent specific and do not vary across choice sets or alternatives. They thus reflect a part of consumer preferences which is consistent across different choices. On the other hand, the ε_{ijs} vary independently across all choice sets and all alternatives. We refer to them as "errors". In the terminology of Fischer et al. (2000), they could also be called preference uncertainty, leading to inconsistent choice behaviour. The ε_{ijs}, allow for boundedly rational behaviour in our setting capturing preference uncertainty, choice inconsistencies, evaluation errors, optimisation errors, etc. One way to interpret this, is to see the multinomial logit framework as a tool to approximate the choice probabilities obtained by some decision rule other than perfect full information comparison of all utility values U_{ij}. The size of the ε_{ijs} (i.e., the variance of the ε_{ijs} relative to the variance of the U_{ij}) then determines the extent to which the actual decision strategy deviates from perfectly rational choice based on full information. Simpler decision strategies then lead to a larger role for the errors.

In a standard multinomial logit framework the ε_{ijs} are assumed to be iid GEV(I). They have the same variance (i.e., are homoskedastic), which, by normalisation, is set equal to $\pi^2/6$. The interpretation of the error terms given above, however, makes it plausible that different choice sets can have different levels of error variance. For example, different levels of complexity may lead to different levels of consumer choice consistency for different choice sets, since they lead to the use of different choice strategies. This is in line with what the results of Fischer et al. (2000) would predict. They find that if evaluation of the alternatives becomes more difficult, ratings require more effort but still become less consistent. We expect the same result for choice consistency. To analyse this, we will incorporate a specific form of heteroskedasticity: the variance of the ε_{ijs} is allowed to be choice set specific (i.e., may depend on s).

To do this in a flexible way, we will allow each choice set s to have a separate scale parameter λ_s that is inversely related to the error variance in that choice set. For our purposes, these scale parameters are auxiliary parameters, which are used in the calculation of the accuracy measures later on. We thus assume that:

1. ε_{ijs} is independent of exogenous variables (X) and random coefficients (β_i,β_{i0}),
2. all ε_{ijs} are independent of each other
3. $\varepsilon_{ijs}/\lambda_s \sim \text{GEV(I)}$

These assumptions imply that, conditional on the random coefficients β_{i0} and β_i, the choice probabilities are given by[2]:

(2.6)
$$P_{is}(c|\beta_{i0},\beta_i) = P(\text{i chooses alternative c in situation s}|\ \beta_{i0},\beta_i) = \frac{\exp(\lambda_s U_{ic})}{\sum_{j=1}^{J(s)} \exp(\lambda_s U_{ij})}$$

This reduces to the familiar multinomial logit choice probabilities if $\lambda_s = 1$ for all choice sets $s = 1,\ldots, S$:

(2.7)
$$P_{is}(c|\beta_{i0},\beta_i) = \frac{\exp(U_{ic})}{\sum_{j=1}^{J(s)} \exp(U_{ij})}$$

Here the summation is over the J(s)+1 alternatives in the given choice situation s (including the 'none'-option). Moreover, for different choice situations, the choices of individual i are

[2] Throughout, we also condition on the exogenous variables X, without mentioning this explicitly.

independent conditional on β_{i0}, β_i. Thus the conditional probability for individual i with choice situations s=1,…, S, given β_{i0}, β_i, to choose J(i,1),…, J(i,S) is:

$$(2.8) \qquad LC_i(\beta_{i0},\beta_i) = \prod_{s=1}^{S} P_{is}(J(i,s)|\beta_{i0},\beta_i,\lambda_s).$$

To identify this model with multiple scale parameters, we set $\lambda_1 = 1$. The location parameters of the utility function (β_{i0}) are normalised by excluding a constant term from X_j.

Estimation

We use smooth simulated maximum likelihood to estimate the model. Conditional on β_{i0} and β_i, i.e., conditional on the U_{ij}, the likelihood contribution of a given respondent is given by (2.8). This is a product of multinomial logit probabilities that are easy to compute. The unconditional likelihood contribution is the expected value of the conditional contribution, with the expectation taken over the (joint) density of β_{i0} and β_i, a (K+1)-dimensional integral for which no analytical expression can be given. This integral is approximated by a simulated mean based upon draws of standard normal error terms which can be transformed into β_{i0} and β_i using (2.3) and (2.4). We use T independent draws for each observation, with independent draws across observations. T is chosen prior to estimation; the results we present are based upon T= 50. The likelihood contribution $L_i = E\{LC_i(\beta_{i0},\beta_i)\}$ is thus approximated by

$$(2.9) \qquad LS_i = 1/T \sum_{t=1}^{T} LC_i(\beta_{i0t},\beta_{it}),$$

where the β_{i0t},β_{it} are the parameter values corresponding to the draws.

The expected value is thus replaced by a simulated sample mean of T draws. The Law of Large Numbers implies that for large T, LS_i will approximate L_i. Instead of maximising the sum of the log likelihood contributions, the sum of the log of the approximated likelihood contributions is maximised. It can be shown that the resulting simulated maximum likelihood estimator is asymptotically equivalent to the ML estimator provided that $T \rightarrow \infty$ fast enough (see Hajivassiliou and Ruud 1994, for example). This implies that standard ways of obtaining ML estimates, standard errors, etc. can be used. Since the ε_{ijs} are not simulated, the simulated likelihood function is a smooth (differentiable) function of the parameters to be estimated.

This has several advantages over the early, non-smooth, simulated maximum likelihood methods (see Hajivassiliou and Ruud 1994).

2.2.2 Measuring Choice Set Complexity

Various studies have found that the outcome of a choice task may be affected by the complexity of the choice situation. Different means for determining the relative complexity of different choice tasks have been suggested. Previous studies have identified several variables that affect complexity: the numbers of attributes and alternatives (referred to as task variables by Johnson and Payne 1985); the level of attribute variability within the alternatives (Shugan 1980, Fischer et al. 2000); the amount of negative correlation between attributes in the choice set (Shugan 1980, Bettman et al. 1990, 1993); the distance between the competing products in utility terms (Shugan 1980). Johnson and Payne (1985) refer to the latter three as context variables. We follow their distinction and discuss task and context based measures of complexity separately.

These two types of measures reflect different features of complexity. If two choice sets have the same number of products and the same number of attributes per product, both will have the same task based complexity, even if attribute values differ between the choice sets. They do not allow complexity to vary with how 'easy' or 'difficult' it is to choose between alternatives with the same number of attributes. On the other hand, context based measures of complexity can differ across choice sets of the same size, since they are based on how consumers value the attributes of the alternatives in the choice set. Context based complexity may or may not increase with the size of the choice set and the number of attributes per alternative. Therefore, both types of measures are required to capture choice set complexity.

Task based complexity

The idea of describing the complexity of a choice task in terms of a set of basic cognitive processes that need to be followed to make a choice has been suggested by several authors such as Huber (1980), Johnson and Payne (1985) and Bettman et al. (1993). Their work draws on Newell and Simon (1972) who suggest that choice strategies can be constructed from a small set of elementary information processes (EIP's). A measure of decision effort can then be measured in terms of the number of EIP's required to select a preferred alternative from a given choice set. Some examples of the EIP's suggested by Newell and Simon (1972) are 'Read', 'Compare', 'Add' and 'Eliminate'.

An estimate of the overall effort required for choosing from a certain choice set is obtained by firstly tallying the number of times each EIP is used for a particular decision process given the choice problem and then summing the total number of operations required to analyse a choice problem. For example, a utility maximising choice rule generally requires more EIP's than simply choosing the cheapest available product.

In this study we follow an EIP based approach to calculate a measure of the task variable based complexity of a choice set. For each choice set we calculate a number based on the number of EIP's required to choose the best alternative based on a utility maximisation rule. Thus, we assign a complexity measure to each choice set based on the minimum number of elementary cognitive processes required to choose the best alternative in this choice set. Different operations may receive different weights in this sum, due to differences in the time required to perform them. Since previous research has suggested that the effort differences between EIP's are relatively small (Bettman et al. 1990), we assign equal weights to all EIP's in summing up over all processes.

Context based complexity

Shugan (1980) distinguishes three choice set based measures of choice complexity[3]. The basis is equation (2.1), stating that an alternative's utility value is the sum of contributions from all the attributes, i.e., of the "attribute utilities". Shugan's model is specified for the case in which the consumer needs to compare only two alternatives. To make this comparison, the consumer randomly selects a number of attributes and examines the corresponding attribute utilities of the two alternatives. The number of attributes that need to be considered for the individual to reach a minimum confidence level that the choice is optimal is driven by the (context based) complexity of the choice. This number will increase with choice complexity that depends positively on the variance of the difference between utilities of a randomly chosen attribute and is negatively related to the absolute value of the mean difference between utilities of a randomly chosen attribute. The variance of the difference can be written as the sum of the variances of the utility of a randomly chosen attribute for each of the two alternatives, minus twice the covariance between the attribute utilities of the two alternatives. Thus Shugan shows that context based complexity is driven by three factors:

1. Variance of a randomly chosen attribute utility for each alternative (VAR),
2. Covariance between the attribute utilities of the two alternatives (COV),
3. (Absolute value of) Difference in utility between alternatives (DIF).

The argument given above implies that increases in VAR make the choice more difficult and thus increase complexity, while increases in COV or DIF reduce complexity.

According to our assumptions in the previous subsection, preferences are heterogeneous across respondents, implying that the U_{ijk} and the three context based complexity measures will vary across respondents. We will work with the estimated values of the β_{ik} for the average respondent, i.e., we will replace the β_{ik} by b_k in (2.3). Thus the choice model in subsection 2.2.1 allows for unobserved heterogeneity via the mixed logit structure, but the choice set specific complexity measures we use will be those for the average respondent. Since we will focus on the relation between choice set complexity and choice accuracy, our measures of choice set accuracy will also be those for the average respondent (see below).

With

(2.10) $U_{jk} = X_{jk}b_k$ (attribute utilities for the average respondent),

(2.11) $U_j = \sum_{k=1}^{K} U_{jk}$ (total utility of alternative j for the average respondent), and

(2.12) $\mu_j = (1/K)\sum_{k=1}^{K} U_{jk}$ (average attribute utility),

the three context based measures for the complexity of comparing alternatives j and j' can be written as

[3] Shugan also discusses the consumer's desired level of accuracy as a factor that influences complexity. In our study we assume this variable to be constant within individuals over all choice sets in the experiment.

(2.13) $$\mathrm{VAR} = (1/K)\sum_{k=1}^{K}(U_{jk} - \mu_j)^2 + (1/K)\sum_{k=1}^{K}(U_{j'k} - \mu_{j'})^2 ,$$

(2.14) $$\mathrm{COV} = (1/K)\sum_{k=1}^{K}(U_{jk} - \mu_j)(U_{j'k} - \mu_{j'}), \text{ and}$$

(2.15) $$\mathrm{DIF} = | U_j - U_{j'} |.$$

In some of the choice situations considered in our survey, more than two alternatives have to be compared. In these cases, the question is which comparisons between pairs of products the consumer needs to make. For a choice set with J alternatives, only J-1 binary product comparisons will be required to determine the optimal product, which is less than the total of all possible pair-wise comparisons. The difficulty of the choice will depend on which comparisons are made. If consumers attempt to make the fewest and simplest possible comparisons, using an average measure will overstate true decision difficulty (c.f. Shugan 1980). If the individual could identify easy comparisons, the least costly combination of comparisons required to reach the individuals particular choice would be more appropriate. Alternatively, some authors have suggested that consumers, when facing a decision task, quickly narrow down the set of alternatives to the top M competing alternatives and invest a lot of effort to compare only these M products (e.g., Gensch 1987). This would imply that in choice sets with $J > 2$ alternatives, the decision-maker reduces the choice set to the $M < J$ most preferred alternatives without much effort, and only once this small set of alternatives is identified, the costly compensatory comparison process is carried out. This smaller set cannot be observed directly by the researcher, but should contain at least the two most attractive alternatives. The appropriate measure would then be the sum over the pair-wise comparisons made between the M alternatives in the 'most preferred' set. However, it cannot be observed which comparisons the consumer makes. Therefore, in this study we calculate the context based complexity measures using the two most attractive alternatives in the 'most preferred' set ($M = 2$) because those two should always be compared by the respondent. In our empirical analysis we checked the sensitivity of our results to this assumption and calculated measures based on the average and sum of all possible comparisons as well as the minimum required number of comparisons for choice sets with more than two alternatives. We found that the results were robust with respect to our choice of measure complexity (Appendix 2.A).

2.2.3 Measuring Choice Accuracy

When an individual is faced with a choice between J products we assume that he or she will attempt to choose the product that provides the highest utility. If this particular product is in fact chosen, then it seems clear that this choice could be referred to as 'accurate'. Likewise, choosing a sub-optimal good could be referred to as 'inaccurate'. However, rather than a binary measure of whether or not the product with the highest utility was chosen, we prefer a continuous measure that in the case of an incorrect choice captures additional information about how close the chosen product was to the optimal product.

Johnson and Payne (1985) study the relation between EIP's and accuracy in a simulation study of different choice rules. For a given choice problem, they find that decision processes requiring more EIP's will lead to higher choice accuracy. To measure the performance of the various decision processes used in their simulations, they define several measures of accuracy of choice heuristics, two of which we adapt for our purposes:

ACC: The expected value (EV) gain of the chosen product following the chosen decision strategy, over random choice, relative to the EV gain of the optimal choice over random choice.

PCC: The gain in the percentage of correct choices following the chosen decision strategy over random choice, relative to the gain in this percentage of the optimal choice over random choice[4].

Both these measures allow for different choice set sizes by comparing the EV of the chosen product and the optimal product with the probability under completely random choice. Using the model assumptions and the notation in the previous subsections, the first measure is expressed as follows.

$$\text{(2.5)} \qquad ACC = \frac{EV_{model} - EV_{random}}{EV_{optimal} - EV_{random}}$$

where

$$\text{(2.5)} \qquad EV_{random} = (1/J)\sum_{j=1}^{J} U_j \qquad \text{(average utility)},$$

$$EV_{optimal} = \max_j V_j, \qquad \text{(optimal utility), and}$$

$$EV_{model} = \sum_{j=1}^{J} \left[\frac{\exp(\lambda_s U_j)}{\sum_{j'=1}^{J} \exp(\lambda_s U_{j'})} U_j \right] \quad \text{(probability weighted mean utility).}$$

The second measure is defined as:

$$\text{(2.5)} \qquad PCC = \frac{PCC_{model} - PCC_{random}}{PCC_{optimal} - PCC_{random}}$$

where

$$\text{(2.5)} \qquad PCC_{random} = 1/J,$$

$$PCC_{optimal} = 1, \text{ and}$$

$$PCC_{model} = \frac{\exp(\max_{j\in J}(\lambda_s U_j))}{\sum_{j'=1}^{J} \exp(\lambda_s U_{j'})}.$$

The accuracy measures ACC and PCC depend on the utility values U_j of the alternatives in the choice set. The model in subsection 2.2.1 implies that preferences are heterogeneous, implying that different respondents have different U_j. We will work with the estimated U_j for the average respondent. This is in line with the complexity measures introduced in the previous subsection, which are also based on the preferences of the average respondent. This two-stage approach allows us to investigate the relationship between choice complexity and choice accuracy based on measures that express consumers' performance relative to optimal and random behaviour. Therefore these measures can be generalised over choice sets of different composition, something which is not possible for the error variance measure theoretically suggested by de Palma et al. (1994) and empirically estimated by Dellaert et al. (1999) and Haaijer et al. (2000).

[4] Johnson and Payne (1985) use the percentage of correct choices directly as a proxy for accuracy. Our definition seems more in line with the other accuracy measure.

2.2.4 The Relationship Between Choice Set Complexity and Consumer Choice Accuracy

Based on previous results in related research, we expect that choice accuracy depends on choice complexity and more specifically, that the higher choice complexity, the lower choice accuracy. In particular, Fischer et al. (2000) find that consumer preference responses become less accurate (as well as taking more effort) as preference judgement tasks become more complex and Dellaert et al. (1999) find that logit model error increases when price based utility differences increase. Although Haaijer et al. (2000) find conflicting results regarding the relationship between effort and accuracy their findings may potentially be explained by differences in strategies between respondents because they do not distinguish between respondent and task based variations in effort. Specifically, Fischer et al. (2000) show that between respondents and for a given task, effort is positively correlated with higher judgement accuracy (i.e., respondents who take more time to respond, also respond more accurately). On the other hand, for a given respondent and for tasks of varying complexity, effort is negatively correlated with judgement accuracy (i.e., the more complex tasks require more effort but still lead to less accurate choices). Since our focus is on within consumer relationships between choice complexity and accuracy, we expect negative effects of complexity on accuracy.

The expected effect of the complexity measures on accuracy then depends on the direction of their relationship with complexity. Increases in EIP's and VAR are expected to increase complexity. A higher EIP value implies that greater effort is required because of the increased number of comparisons necessary to get to the best option (Bettman et al. 1993), therefore complexity increases with EIP's. Similarly, if the variance between the utilities of the different attributes of an alternative increases, the complexity of the choice also increases (Shugan 1980, Fischer et al., 2000). Increases in COV and DIF on the other hand are inversely related to complexity. The higher the covariance between the attribute utilities of different alternatives in the choice set, and, the further apart the utilities of the alternatives in the choice set, the easier it is to determine the alternative with the highest utility (Shugan 1980). Thus, based on the complexity effects of the different measures we expect choice accuracy to decrease with increases in EIP's and VAR and to increase with increases in COV and DIFF.

To investigate the empirical validity of these hypothesised relationships, least squares regressions are performed. The units of observation are the 56 separate questions in the survey. The dependent variables are the accuracy measures for the average respondent, discussed in subsection 2.2.3. The independent variables are the complexity measures for the average respondent, as discussed in subsection 2.2.2.

2.3 Empirical Analysis

2.3.1 Data

A conjoint choice survey was designed to empirically examine the impact of shifts in complexity on consumer choice accuracy. Consumers were asked to choose between various hypothetical yoghurt products, each described by up to 7 attributes: Price, Percentage of fruit, Biological cultures (yes/no), Fat content (percentage), Creamy flavour (yes/no), Recyclable Packaging (yes/no), and All natural ingredients (yes/no). The survey varied the level of complexity by introducing several different versions. The preamble to the survey asked respondents to imagine that they were having lunch in a self-service restaurant and deciding which yoghurt to buy for dessert. They were instructed that yoghurts were identical on all attributes not mentioned in the alternatives and that they were available in all their favourite fruit-flavours. Respondents also had the base option of not choosing any of the yoghurt products in the choice set.

The survey was divided into 2 parts of 8 choice sets each. The first part consisted of 8 choice sets of two alternatives and the base of not buying either of the alternatives. The alternatives of the choice sets were constructed based on a randomised main effects design using only 2^3 fraction of a 2^7 full factorial design with its fold-over (see Louviere and Woodworth 1983). This first part of the survey was identical for all respondents. For the second part of the survey respondents were randomly assigned to one of 6 treatment conditions. Respondents in each of the 6 groups were presented with a further 8 choice sets. Choice sets in the different conditions were constructed so as to vary systematically their EIP, VAR, COV and DIFF scores. In particular, differences in complexity were created by altering the number of attributes (condition 1), the number of alternatives (conditions 2 and 3), both the number of alternatives and covariance between alternatives (condition 4), and the relative difference in attribute levels in the choice sets (condition 5). One control condition (condition 6) identical in structure to the choices in the first part of the survey was included also. Table 2.1 summarises this structure, while table 2.2 provides the attributes and their levels in the different conditions.

Table 2.1: Description of choice task per experimental condition

	Number of Choice sets	*Number of attributes*	*Number of alternatives*	*Attribute level variation*	*Number of observations*
Base	8	7	2	Base level	909 (all)
Condition 1	8	3	2	Base level	153
Condition 2	8	7	4	Base level	163
Condition 3	8	7	6	Base level	137
Condition 4	8	7	3	Base level	164
Condition 5	8	7	2	High difference	145
Condition 6 (control)	8	7	2	Base level	147

Choice sets in condition 1 of the second part were constructed on the basis of a 2^3 full factorial design in 4 profiles with its fold-over. This 4-profile design was repeated once in a different order to construct 8 choice sets. Choice sets in conditions 2 and 3 were constructed starting from the same 2^3 fraction of a 2^7 full factorial as used in part one. Additional alternatives (3 and 5) were added to the choice sets by randomly assigning alternatives from this same design. Strictly dominated alternatives were swapped with alternatives assigned to other choice sets. Condition 4 differed from the previous two in that one dominated alternative was added to the choice sets used in part 1. These alternatives differed from one of the alternatives in the choice set in terms of only one of the 7 attributes, which was set at the less attractive level. Choice sets in conditions 5 and 6 were constructed identically to those in part 1.

Respondents in the survey were participants in the CentER*data* panel, an ongoing consumer panel in The Netherlands run through Tilburg University. The panel consists of approximately 2000 individuals and is largely representative of the Dutch population in terms of age, sex, income, education and geographical location. It runs on a weekly basis and respondents participate voluntarily. Respondents were screened on being yoghurt consumers. Of the 978 members of this subgroup a total of 909 completed the survey successfully.

Table 2.2: Attributes and levels used in the experiment

		Description of levels	
Attribute	*Present in conditions*	*Base condition*	*High difference condition*
Price	1-6	NLG 1.90	NLG 2.10
		NLG 1.50	NLG 1.30
Fruit content	1-6	10% fruit	15% fruit
		5% fruit	5% fruit
Biological cultures	2-6	Contains biological cultures	Contains biological cultures
		Contains no biological cultures	Contains no biological cultures
Artificial flavouring	2-6	Contains artificial flavouring	Contains artificial flavouring
		Contains no artificial flavouring (all natural)	Contains no artificial flavouring (all natural)
Creamy taste	2-6	Creamy taste	Creamy taste
		Regular taste	Regular taste
Fat content	1-6	0.5% fat content	0.5% fat content
		3.5% fat content	7.5% fat content
Recyclable packaging	2-6	Yoghurt container is recyclable	Yoghurt container is recyclable
		Yoghurt container not recyclable	Yoghurt container not recyclable

2.3.2 Results

To calculate the appropriate measures of choice accuracy and complexity, first the heteroskedastic random coefficients model (subsection 2.2.1) was estimated using data from all conditions in parts 1 and 2. The model allowed for heterogeneity in taste between respondents as well as different random error scales (λ) for all choice sets. The estimates of the main effects and the standard deviations of the random coefficients are presented in table 2.3. All main effects were significant at the 95% confidence level and had signs as expected. The standard deviations of all random coefficients were rather accurately determined, with their confidence intervals bounded away from zero, thus indicating significant heterogeneity across respondents.

Table 2.3: Choice model estimates*

Parameter	*Estimate*	*t-value*
Intercept	-2.611	-11.982
Price	-0.974	-11.288
Fruit content	0.154	11.794
Biological cultures	0.292	9.028
Artificial flavouring	-0.889	-11.866
Creamy taste	0.365	10.411
Fat content	-0.385	-12.762
Recyclable packaging	0.568	11.015
Standard deviations of random coefficients		
SD intercept	-1.670	-12.629
SD price	-0.444	-8.684
SD fruit content	0.074	8.655
SD biological cultures	0.113	3.230
SD artificial flavouring	-0.575	-11.618
SD creamy taste	0.469	11.041
SD fat content	-0.286	-12.847
SD recyclable packaging	-0.123	-4.102

*Results for heteroskedastic random coefficients model, for estimates of error scale differences between choice sets (2.8) see values of λ in table 2.4; log-likelihood = -11831.56, BIC = 11616.97.

The error scale differences over all choice sets were also estimated and are presented in table 2.4. A likelihood ratio test of the model with and without these error scale estimates showed that the effect of the error scale estimates was highly significant (a Chi-squared test value of 388.72 at 55 degrees of freedom), implying that there were indeed differences in error between choice sets. This result is in line with earlier results by Dellaert et al. (1999) and Haaijer et al. (2000) who also observed significant variations in error scales over choice sets of different complexity.

Table 2.4 also presents the values of the different complexity measures calculated for each choice set in the different choice conditions. There is considerable variation in the value of these measures as was intended through the structure of the choice experiments in the survey. The correlations between the measures were all below 0.40 except for the correlation between VAR and COV, which was 0.66.

Table 2.4: Complexity measures and scale parameter estimates

Choice set & Question	*EIP's*	*J*	*K*	*VAR*	*COV*	*DIFF*	λ
Base 1	41	3	7	2.352	0.816	0.007	1.000[5]
Base 2	41	3	7	2.356	0.814	0.001	1.104
Base 3	41	3	7	2.354	0.815	0.003	1.140
Base 4	41	3	7	2.308	0.838	0.097	1.148
Base 5	41	3	7	2.349	0.817	0.013	1.13
Base 6	41	3	7	2.141	0.921	0.430	0.910
Base 7	41	3	7	2.216	0.884	0.279	0.972
Base 8	41	3	7	2.355	0.814	0.002	1.208
1.1	17	3	3	4.247	1.807	0.378	1.509
1.2	17	3	3	4.004	1.928	0.863	1.603
1.3	17	3	3	4.436	1.713	0.000	1.528
1.4	17	3	3	4.383	1.739	0.106	1.563
1.5	17	3	3	2.167	0.797	0.087	1.383
1.6	17	3	3	2.211	0.776	0.000	1.811
1.7	17	3	3	2.109	0.827	0.205	1.260
1.8	17	3	3	1.917	0.922	0.587	1.569
2.1	83	5	7	2.460	1.193	0.002	1.604
2.2	83	5	7	2.178	0.771	0.017	1.704
2.3	83	5	7	2.676	1.224	0.043	1.374
2.4	83	5	7	1.433	0.587	0.013	1.662
2.5	83	5	7	2.278	1.103	0.004	1.316
2.6	83	5	7	2.115	0.732	0.000	1.881
2.7	83	5	7	2.062	0.945	0.099	1.141
2.8	83	5	7	2.860	1.294	0.000	1.919
3.1	125	7	7	2.959	1.286	0.001	1.596
3.2	125	7	7	1.894	0.833	0.012	1.540
3.3	125	7	7	2.292	0.990	0.089	1.355
3.4	125	7	7	1.610	0.714	0.030	1.523
3.5	125	7	7	2.676	1.224	0.043	1.288
3.6	125	7	7	2.214	0.987	0.000	1.611
3.7	125	7	7	2.278	1.103	0.004	1.521
3.8	125	7	7	1.433	0.587	0.013	1.198
4.1	62	4	7	2.105	0.901	0.245	1.198
4.2	62	4	7	1.547	0.651	0.041	1.692

[5] Not estimated, but normalized to 1.

4.3	62	4	7	2.355	0.814	0.002	1.576
4.4	62	4	7	2.544	1.262	0.003	1.212
4.5	62	4	7	2.356	0.814	0.001	1.622
4.6	62	4	7	2.354	0.815	0.003	2.265
4.7	62	4	7	2.629	1.237	0.026	1.407
4.8	62	4	7	2.352	0.816	0.007	1.698
5.1	41	3	7	4.271	0.959	0.085	1.204
5.2	41	3	7	4.194	0.997	0.240	0.616
5.3	41	3	7	4.314	0.937	0.000	1.154
5.4	41	3	7	4.179	1.004	0.269	1.114
5.5	41	3	7	4.215	0.987	0.198	0.564
5.6	41	3	7	3.686	1.251	1.256	0.686
5.7	41	3	7	3.945	1.122	0.739	0.298
5.8	41	3	7	4.313	0.937	0.001	1.165
6.1	41	3	7	2.141	0.921	0.430	0.940
6.2	41	3	7	2.308	0.838	0.097	1.026
6.3	41	3	7	2.355	0.814	0.002	1.182
6.4	41	3	7	2.216	0.884	0.279	0.992
6.5	41	3	7	2.356	0.814	0.001	1.342
6.6	41	3	7	2.354	0.815	0.003	0.849
6.7	41	3	7	2.349	0.817	0.013	1.060
6.8	41	3	7	2.352	0.816	0.007	1.226

The complexity measures were then regressed on the ACC and PCC scores calculated for each choice set. These scores were also based on the logit model estimates in table 2.3 and the values of λ in table 2.4 (see figure 2.1 for a summary of the model and measurement structure). The results of these two regression analyses are presented in table 2.5. For the ACC measure all parameters for the context based complexity measures were significant and had signs as expected. Accuracy decreased with VAR (variance of the attribute utilities in the choice set alternatives) and increased with COV (covariance between the attribute utilities in the choice set alternatives) and DIF (difference in utility between the alternatives in the choice set). The EIP complexity measure however, was not significantly different from zero. For the PCC measure the estimates for the context based complexity measures also had signs as expected but only the parameter for DIF was significant. EIP again was not significant.

To test the sensitivity of the results to the definition of our proposed measures of VAR, COV and DIF, we also ran regressions using some alternative specifications for these measures. In particular, we calculated measures based on the average and sum of all possible comparisons as well as the minimum required number of comparisons per choice set. The results were identical in sign and similar in terms of significance for all measures (Appendix 2.A).

Table 2.5: Accuracy model estimates: ACC and PCC*

	Constant	*EIP's*	*VAR*	*COV*	*DIF*	*Adj.* R^2
ACC	0.55	0.00	-0.07	0.24	0.32	0.408
	(7.47)	(0.89)	(-2.69)	(3.24)	(4.54)	
PCC	0.47	0.00	-0.06	0.10	0.70	0.437
	(3.92)	(0.07)	(-1.42)	(0.82)	(6.14)	

* OLS regressions based upon 56 observations; t-values in parentheses.

Thus across the two measures we observe that context based complexity affects accuracy in a similar way to the effects observed for consumer judgements by Fischer et al. (2000) and to those suggested by Shugan (1980). These two studies also stressed the effects of context based aspects of complexity. The expected effects of task based complexity on accuracy are not supported by our study.

More generally, our findings suggest that consumers adapt their decision strategy in response to shifts in task variables, but not in response to shifts in context variables. They may base their decision on how much effort to put into the choice process on task variables (number of alternatives and attributes) rather than on context variables. If consumers increase their effort sufficiently to keep the accuracy level constant when task based complexity is increased but not if context based complexity is increased, this behaviour can explain the fact that accuracy is affected by context variables but not by task variables. This explanation is also in line with Johnson and Payne's (1985) observation that the effort involved in following a certain choice strategy depends on task variables only, while given effort, level of accuracy is driven by context effects.

2.4 Discussion and Conclusion

We have investigated the relation between choice set complexity and choice accuracy, using conjoint choice data that varied in terms of choice context. To distinguish choice inaccuracy from consumer heterogeneity, we have used a mixed logit framework. We have assumed that heterogeneous preferences are respondent specific and thus do not vary over the questions for a given respondent, while choice errors are independent over the questions. Thus our definition of choice errors also includes inconsistencies due to choice uncertainty. By including question specific variances of the choice errors, we allow for accuracy variation in a flexible way. To our knowledge, we are the first to integrate these complexity measures in an empirical mixed logit framework of conjoint choice responses. On the other hand, there have been several simulation studies on the relation between complexity, effort and accuracy, and there is some recent empirical work on inaccuracy or preference uncertainty in judgement ratings data, but not in choice.

Both our main results are in line with the existing literature. We find that context based complexity measures significantly relate to choice accuracy with the expected signs. On the other hand, we find no effect of task based complexity on choice accuracy. An interpretation of this result is that larger task based complexity is fully compensated by increased effort, while larger context based complexity is not. The current data do not allow for a direct test of this. Future work could use data on effort (such as the time to make the choices) to extend the empirical analysis (see chapters 4 and 5).

A potential implication of our findings for marketing management may be that brands that are positioned closely to one another (DIF is small) and for which product attribute utilities are not strongly correlated (VAR is large and/or COV is small) may be less well equipped to benefit from product or price improvements. The reason is that consumers' choice responses to those changes are found to be less 'accurate', i.e., they are less well in line with consumers' underlying preferences. These inaccuracies may be of benefit to other brands which do not improve and which may find that they can maintain a more stable market share than if consumer choices were fully accurate expressions of their preferences. On the other hand brands which can distinguish themselves in terms of utility (DIF is large) and that have a consistent set of attributes (VAR is small) can gain additional leverage on their preferential position, because consumers choose these brands more accurately.

Appendix

2.A: Alternative Complexity Calculations

Table 2.6: Accuracy model variations: ACC and PCC*

Comparisons Used for Complexity Calculations	*Dependent Variable*	*Constant*	*EIP's*	*VAR*	*COV*	*DIF*	*Adj.* R^2
Comparison of top two goods	ACC	0.55	0.00	-0.07	0.24	0.32	0.408
		(7.47)	(0.89)	(-2.69)	(3.24)	(4.54)	
	PCC	0.47	0.00	-0.06	0.10	0.70	0.437
		(3.92)	(0.07)	(-1.42)	(0.82)	(6.14)	
Sum of comparisons with best good	ACC	0.67	-0.00	-0.06	0.12	0.29	0.524
		(19.95)	(-0.47)	(-2.16)	(1.81)	(6.06)	
	PCC	0.51	-0.00	-0.03	-0.01	0.57	0.578
		(9.75)	(-0.35)	(-0.76)	(-0.12)	(7.73)	
Average of comparisons with the best good	ACC	0.51	0.00	-0.07	0.27	0.36	0.499
		(5.71)	(1.00)	(-2.58)	(2.34)	(5.08)	
	PCC	0.46	-0.00	-0.05	-0.01	0.80	0.562
		(3.36)	(-0.18)	(-1.11)	(-0.05)	(7.28)	
Sum over all comparisons	ACC	0.64	0.00	-0.10	0.21	0.44	0.503
		(14.20)	(0.58)	(-2.02)	(1.78)	(5.43)	
	PCC	0.53	-0.00	-0.01	-0.00	0.77	0.393
		(6.36)	(-0.63)	(-0.14)	(-0.00)	(5.14)	
Average of all comparisons	ACC	0.51	0.00	-0.13	0.45	0.73	0.469
		(6.10)	(1.25)	(-2.39)	(3.00)	(5.31)	
	PCC	0.41	-0.00	-0.09	0.22	1.40	0.451
		(2.88)	(-0.05)	(-1.02)	(0.89)	(6.10)	
(Average of all comparisons)×(j-1)	ACC	0.64	-0.00	-0.13	0.29	0.76	0.575
		(19.81)	(-0.08)	(-2.62)	(2.63)	(7.30)	
	PCC	0.47	-0.00	-0.08	0.12	1.31	0.514
		(8.27)	(-0.16)	(-0.94)	(0.64)	(7.13)	

* OLS regressions based upon 56 observations; t-values in parentheses.

Chapter 3

Combining and Comparing Consumers' Stated Preference Ratings and Choice Responses

In this chapter we develop and test an econometric model for combining choice and preference ratings data collected from the same set of individuals. Choice data are modelled using a multinomial logit framework, while preference data are modelled using an ordered response equation. Individual heterogeneity is allowed for via random coefficients providing a link between the choice and ratings data. Parameters are estimated by simulated maximum likelihood. An application of the model to consumer yoghurt choice in The Netherlands found that ratings based preference estimates differ significantly from choice based estimates, but the correlation between random coefficients driving the two is very strong.

3.1 Introduction

When modelling consumer preferences in the random utility framework a researcher has a number of econometric techniques available. With *revealed preference* (RP) data, i.e., actual consumer purchase data, the techniques are often determined by the nature of the available data. However, if *stated preference* (SP) data, which represent consumer decisions in hypothetical market situations, are to be collected, the researcher has the flexibility to choose which modelling approach to apply and to design choice experiments in line with this approach. In the marketing and transportation research literature, conjoint analysis is a frequently applied SP research technique, which encompasses analysis of three types of consumer preference data: ratings, rankings and choice data (e.g., Ben-Akiva et al. 1992, Bradley and Daley 1994, Haaijer et al. 1998, Louviere et al. 1993, Louviere 1994). The models used to estimate preferences for these data types range from OLS to ordered probit or ordered logit for ratings and multinomial probit or logit for the data on choices and rankings. Other SP methods of preference elicitation, more commonly found in the field of environmental economics, are contingent valuation (CV) methods that address individuals' willingness to pay (WTP) for certain environmental policy changes (e.g., Adamowizc et al. 1994, Carson et al. 1996). Again there are a number of different models that support estimation of preference models based on CV type response data which may be implemented depending on the type of data collected, for example, single-bounded, multiple-bounded and open-ended approaches to measuring WTP.

Although the approaches differ considerably, they are generally wielded for the same purpose of eliciting consumer preferences, and, whilst methodology changes, for the same set of underlying preferences, utility estimates based on any of these models would ideally be statistically indistinguishable (after possible correction for task based biases). Therefore, if two differing types of data sets relating to the same consumers' preferences are available, an efficient use of the available data suggests that we should be able to estimate the same preference parameters from both sets simultaneously. Herein lies the concern of the current work: providing a model enabling estimation of the same consumers' utility functions from different types of stated preference data and to analyse the differences in utilities between response modes if they occur. In particular, we examine two of the most commonly used SP responses: preference ratings and choice data.

Research interest in combining sources of preference data has recently increased (e.g., Hensher et al. 1999). There are various potential advantages to this, such as the opportunity to exploit the various strengths and weaknesses associated with each data type and the possibility to test whether the decision processes underlying responses to the data types are the same. If this hypothesis is rejected, a joint model can be used to analyse where partial differences between consumer utilities driving ratings and choice come from, and to trace question specific psychological factors that bias the utility indexes. Data pooling may also be required for implementation of new and more complex models recently developed in consumer research, such as models for examining the dynamic aspects of consumer processes, where panel data may be required (Louviere et al. 1999).

Furthermore, if different data sets arise from identical underlying consumer utilities, joint estimation will provide more efficient results. Another goal of joint estimation therefore is an efficiency gain. If both ratings and choice data contain useful information on the underlying preferences of respondents, using both of them will help to get more accurate estimates of the parameters driving the utility function. Specifically, when comparing ratings and choice data, an advantage of ratings data is that it enables unbiased estimation of parameters at the individual level through the use of ordinary least squares. Disaggregate estimation is less desirable with choice data, as the most commonly used multinomial logit (MNL) model is biased for a small number of questions per respondent and estimates may even be infinite (Bunch and Batsell 1989). Thus cost-reduction may also be achieved in data collection if fewer ratings than choice questions are required to get to the same level of statistical reliability, and if respondents find it easier to respond to additional ratings questions than additional choice questions.

The aim of this chapter is to provide a model, consistent with random utility theory, for combining data on SP ratings and choice responses for the same individuals. In doing so, we do not treat the data sets as independent, but allow for correlation between the choices and the ratings of the same respondents. We model the ratings data with an ordered probit equation and the choice data via the multinomial logit model. Our modelling approach allows for heterogeneity across preferences in the population of consumers through random coefficients. This is advantageous because it allows for correlations between the choices and ratings for the same individual. According to random utility theory, the same consumer utility function should determine the outcomes in both data sets, and thus the preference parameters driving choice and ratings data should be identical. This leads to testable restrictions on the parameters in the ratings and choice parts of the model.

We test the validity of this assertion, using data on yoghurt choices and ratings from a large consumer panel. We find that although consumers' preference ratings and choices are significantly correlated, there are significant differences in the standard deviations and some of the means of the random coefficients. Possible explanations for the observed differences drawn from the economic and psychological literatures are tested and discussed.

The remainder of the chapter is organised as follows. Section 3.2 provides a brief review of the literature. Section 3.3 introduces the model. Data and results are given in section 3.4. Some potential psychological and economic explanations for our findings are presented in section 3.5. Section 3.6 concludes.

3.2. Literature Review

Previous research on comparing SP ratings and choices has focused mainly on the predictive performance of models estimated on the different types of responses. In particular, Elrod et al. (1992) found that ratings and choice data generally perform equally well in terms of prediction at the aggregate level. The few studies examining the equivalence of the estimated preference parameters were predominantly done in the area of environmental economics. For example, Boxall et al. (1996) compared estimation results from choice data to those based on a CV WTP data set. They compare the welfare estimates based on the two data sets and find that the CV WTP estimate is over 20 times higher than the alternative SP choice experiment suggests. The authors suggest the dramatic difference could be due to respondents misunderstanding the scenario, or a bias due to 'yea-saying', but believe that it is more probably a result of the respondents ignoring substitution possibilities in the CV questionnaire. Another study comparing data based on different elicitation methods is Cameron et al. (1999) who combine data arising from one RP choice, three SP choice tasks, one SP rating task and two WTP tasks, administered to seven independent samples. Their results indicate that once scale differences are allowed for, the hypothesis of equivalence of underlying utilities cannot be rejected across the choice and rating data sets, but do differ between the willingness to pay responses and the other responses. Likewise, Boyle et al. (1996) compare SP choice with WTP responses using three independent samples and find differences in scale between all data sets and differences in (relative) mean parameter estimates between two of their three data sets.

Other comparisons of preference elicitation methods have focused on the comparison of choice based models. A distinction can be made between papers that combine RP with RP or SP with SP (Morikawa 1989, Hensher and Bradley 1993, Swait et al. 1994) and those combining RP and SP (Louviere et al. 1993, Adamowicz et al. 1994, Bradley and Daley 1994). Both streams examine the hypothesis that consumer utilities underlying the pooled choice data sets are identical. The majority of these studies have found that after correcting for scale differences in error variance, the hypothesis of common preferences is not rejected.

In summary, the empirical evidence to date suggests that within a given response format, consumer utilities are mostly stable, but that there may be biases associated with different survey response formats causing differences in response and/or utilities, especially between WTP and choice data responses. The difference between SP ratings and choices however, is not as well explored. Predictions on hold out consumer choice tasks based on SP ratings and choices do not seem to be seriously affected by response differences (Elrod et al. 1992). Also, after correcting for scale differences Cameron et al. (1999) could not reject the hypothesis of equal parameters underlying SP ratings and choice.

However, to date no econometric model has been proposed to combine and compare consumer ratings and choice data that allows for correlation between observations from the same individual. This limits the interpretation and testing of utility estimates based on SP ratings and choice, because individuals' responses to the two types of SP tasks cannot be integrated. It also limits possible efficiency gains both in terms of statistical estimation efficiency and in terms of data collection. Furthermore, developing insights into complex consumer behaviour may require collection of multiple data types of the same individual in which case models allowing for individual responses to be correlated will be useful also.

3.3 Modelling Consumer Stated Preference Ratings and Choice Responses

In this section we present the econometric model to analyse consumers' SP ratings and choice data. We address issues of identification and scaling between models based on ratings and the choice data (cf. Swait and Louviere 1993). For clarity of exposition, we first discuss the (more intuitive) model of consumer choice and then extend our model to include rating responses. We use the following notation:

i respondent ($i=1,\dots,N$); N is the total number of respondents

k attribute ($k=1,\dots,K$); K is the total number of attributes

s choice situation ($s=1,\dots,S$); S is the total number of choice situations

j alternative ($j=0,1,\dots,J(s)$); $J(s)$ is the number of alternatives in choice situation s

J total number of different alternatives across all choice situations

$X_j = (x_{j1},\dots,x_{jK})'$ vector of attributes of alternative j; X_j does not include a constant.

3.3.1 Model for Choice

Let the utility of alternative j for respondent i be given by:

(3.1) $$U_{ij} = X_j'\beta_i \qquad j=1,\dots,J$$

The vector of slope coefficients $\beta_i=(\beta_{i1},\dots,\beta_{iK})'$ may vary across respondents. It reflects unobserved heterogeneity in the marginal utilities of the attributes. Let alternative $j=0$ be the so called 'none'-option of not choosing any of the alternatives j. Its utility to respondent i is given by

(3.2) $$U_{i0} = \beta_{i0}$$

The 'none'-option differs from the other alternatives in the sense that it does not have any attribute values. An equivalent way of modelling this utility would be to normalise the utility of the numeraire to 0, and add a respondent specific base level utility (which does not vary over attributes or alternatives) to the utility values of all the other alternatives.

The β_i and β_{i0} are treated as random coefficients, using the following specification:

(3.3) $$\beta_{ik} = b_k + u_{ik}, \quad k=0,\ldots,K,$$

(3.4) $$u_i = (u_{i0},u_{i1},\ldots,u_{iK}) \sim N(0,\Omega)$$

The unobserved characteristics of respondent i enter through u_{ik}. We assume that the u_{ik} are drawn from a (K+1)-variate normal distribution with mean zero. Note that β_i is respondent specific but not choice situation or alternative specific. It is thus assumed that the same β_i is used by respondent i in all choice situations. The parameters in the $(K+1)\times(K+1)$ matrix Ω are to be estimated. For computational convenience, we will assume that Ω is diagonal, so that only (K+1) standard deviations (ω_k) need to be estimated. Since the random coefficients β_{i0} and β_i (or the u_{ik}) do not vary with choice situations or alternatives, and since they are independent across individuals, the correlation structure of choices across individuals, choice situations, and alternatives identifies the variances of the random coefficients.

In constructing a model for choice probabilities, we follow the usual multinomial choice framework in that choices are based upon the sum of utility values U_{ij} and errors ε_{ijs}:

(3.5) $$U_{ijs}^* = U_{ij} + \varepsilon_{ijs} \qquad j=0,\ldots,J(s),\ s=1,\ldots,S$$

Respondent i chooses alternative c in choice situation s if and only if $U_{ics}^* \geq U_{ijs}^*$ for all j in the given choice situation. We assume that:

1. ε_{ijs} is independent of exogenous variables (X) and random coefficients (β_i, β_{i0}).
2. $\varepsilon_{ijs} \sim GEV(I)$, and
3. All ε_{ijs} are independent of each other.

These assumptions imply that, conditional on the parameters β_{i0} and β_i[1], we get the familiar multinomial logit choice probabilities:

(3.6) $$P_{is}(c|\beta_{i0}, \beta_i) = P(\text{i chooses alternative c in situation s}|\ \beta_{i0}, \beta_i) = \frac{\exp(U_{ic})}{\sum_{j=0}^{J(s)} \exp(U_{ij})}.$$

Here the summation is over the J(s)+1 alternatives in the given choice situation s (including the 'none'-option). Moreover, for different choice situations, the choices of individual i are

[1] Throughout, we also condition on the exogenous variables X, without mentioning this explicitly.

independent conditional on β_{i0},β_i. Thus the conditional probability for individual i with choice situations s = 1,..., S, given β_{i0},β_i, to choose J(i,1),..., J(i,S) is:

$$LC_i(\beta_{i0},\beta_i) = \prod_{s=1}^{S} P_{is}(J(i,s) \mid \beta_{i0},\beta_i) \tag{3.7}$$

Normalisation and identification

As usual, the scale of the utility function is normalised by a specific choice of the scale of ε_{ijs}. This is the same as in a standard logit or multinomial logit model. The location parameters of the utility function (β_0) are normalised by excluding the constant from X_j. As a consequence, all parameters determining the distribution of the random coefficients are identified[2].

3.3.2 Model for Ratings

We refer to a task as a SP ratings task if an individual assigns a score on a scale (graphically or numerically) to a product, indicating the individual's preference for that product. SP ratings tasks differ from choice tasks in several respects. From the modeller's perspective, two important differences are that ratings responses are numerical or ordinal in nature, whereas choices are nominal, and that ratings are asked separately for each product, while choices often involve trade-offs between multiple products. To make the theoretical link between SP choices and ratings responses we assume that the ratings answer is based upon comparing the utility value of product j, (U_{ij}), to the utility of the numeraire (i.e., not buying the product) (U_{i0}). We will show below that this assumption is plausible given the wording of the ratings questions in our survey. Thus, we assume that an error free rating would be based upon $U_{ij} - U_{i0}$. Analogously to the error terms ε_{ijs} in the choice model, we allow for a random error term, v_{ij}, and assume that the observed ratings are based upon

$$U_{ij} - U_{i0} + v_{ij} \tag{3.8}$$

We assume that the error terms v_{ij} are mutually independent, independent of the exogenous variables, and independent of all other error terms in the model. Moreover, we assume they

[2] It would also be possible to add alternative specific error terms which are independent across alternatives and individuals, but remain the same for a given individual and alternative across choice sets. In our empirical work, we included these effects, but found that they did not play a significant role.

are all drawn from the same normal distribution[3] with mean 0 and variance σ_v^2. The v_{ij} can be seen as evaluation errors on the ratings. Consumer heterogeneity enters through U_{ij}, i.e., through the random coefficients β_{i0} and β_i. Correlation between choices and ratings comes in through these random coefficients. It therefore seems reasonable to assume that the v_{ij} are independent of the GEV(I) errors ε_{ijs} in the choice evaluations.

Often, rating responses are grouped in classes, either due to a categorical response scale introduced by the researcher or by the respondents' natural tendency to prefer certain numbers over others (e.g., 10, 20, 30, etc). In what follows, we treat the observed ratings as an ordered categorical variable with R possible outcomes, say r = 1,..., R. If the original ratings variable in the data is continuous, we first summarise it into a categorical variable before applying our model. We will come back to this below in discussing our data. We thus use an ordered response specification to model in which category the ratings are, similar to an ordered probit model. There is no reason why the scale of the utility function in the choice part (which is determined by normalising the variance of the error terms in the choice part) would be the same as the scale of the ratings. Instead, it seems reasonable to allow for an unknown monotonic (possibly non-linear) transformation that transforms a utility index into a rating. This can be achieved in a flexible and simple way, by allowing for unknown bounds of the categories in the ordered response model.

To be precise, we assume that the ratings on a continuous scale underlying the categorical ratings are based upon the following unknown strictly increasing function g of the index in (3.8).

(3.9) $$R_{ij}^* = g(U_{ij}-U_{i0}+v_{ij})$$

We assume that g is the same for all respondents. As will be shown below, the assumption is needed to get the tractable ordered response model with fixed category thresholds. The assumption of fixed category thresholds is fairly standard in the ordered response models literature.

To transform the continuous (unobserved) variable R_{ij}^* into an observed categorical variable R_{ij} with R possible outcomes, we follow the same procedure as in a standard ordered

[3] Alternatively, a GEV(1) distribution could have been used which would have been somewhat more in line with the choice part of the model. In the literature on ratings, however, the normal distribution is more common. We do not expect any substantial differences for the results.

response model. We partition the real line into R ordered categories, bounded by R-1 thresholds, and follow the standard assumption that these thresholds are common to all respondents. For notational convenience, the thresholds are denoted by $g(m_1)$, …., $g(m_{R-1})$. The link between R_{ij}^* and the observed categorical ratings, is now given by

$$R_{ij} = r \text{ if and only if } g(m_{r-1}) < R_{ij}^* \leq g(m_r) \quad (r=1, \ldots, R) \tag{3.10}$$

Using (3.9) and the fact that g is strictly increasing, this can be rewritten as

$$R_{ij} = r \text{ if and only if } m_{r-1} < U_{ij}-U_{i0} + v_{ij} \leq m_r \tag{3.11}$$

The thresholds ($-\infty = m_0 <$) $m_1 < \ldots < m_{R-1}$ ($< m_R = \infty$) are unobserved parameters which can be estimated. Note that this procedure allows for an unknown strictly increasing transformation g, but g itself does not need to be estimated. This is the advantage of treating the ratings as an ordered categorical variable. Allowing for arbitrary values $m_1,\ldots, m_{R-1}$ corresponds to using a flexible function g. To attain the same flexibility with a regression model for ratings observed on a continuous scale, it would be necessary to estimate g non-parametrically. We avoid this, and, instead, only need the R-1 threshold values $m_1,\ldots, m_{R-1}$. These values are estimated as separate (ancillary) parameters.

Normalisation and identification

If a model for the ratings only would be estimated, some normalisation of scale and location would be necessary. One way to achieve this would be to fix U_{i0} and σ_v^2 *a priori*. If, however, we simultaneously use the choice data (and use the same utility values in (3.8) as in (3.5)), the normalisation is already imposed in the choice part of the model: the scale of U_{ij} is determined by the normalisation of the variance of ε_{ijs}. The constant term in the ratings corresponds to β_{i0} in the choice model, and is also identified (because the constant term is excluded from the other U_{ij}). In other words: there is no need for further normalisation to identify the joint model for choice and ratings, and all the thresholds m_r (r = 1, …, R-1) can be estimated without imposing further restrictions.

3.3.3 Estimation and Testing

In the joint estimation of the two parts of the model, using both choice and ratings data, the link between choice and ratings comes in through the random coefficients. For a given respondent, β_{i0} and β_i enter both the choice and the ratings parts of the model. This distinguishes the estimation problem from the problem of estimating parameters using two or more independent samples, which is the more common situation in this literature (e.g., Boyle et al. 1996, Cameron et al. 1999).

We use smooth simulated maximum likelihood to estimate the model and to do inference. The likelihood is described below. A discussion of the estimation procedure and how it relates to standard estimation procedures is given in Appendix 1.

Likelihood contributions

Conditional on β_{i0} and β_i, i.e., conditional on the U_{ij}, the probability that respondent i gives a specific series of M categorical ratings, can be written as the product of univariate normal probabilities (as in an ordered probit model). Moreover, conditional on β_{i0} and β_i the ratings are independent of the choices, so the conditional probabilities of the observed categorical ratings and the observed choices, given β_{i0} and β_i, are the product of choice and ratings contributions. Conditional on β_{i0} and β_i, the likelihood contribution of a given respondent is therefore a product of MNL probabilities (choices) and univariate normal probabilities (ratings). The unconditional likelihood is the expected value of the conditional contribution, with the expectation taken over the (joint) density of β_{i0} and β_i, a (K+1)-dimensional integral for which no analytical expression can be given.

A test for preference stability

There are several strategies for constructing tests of whether ratings and choice are indeed driven by the same preferences. A test which does not require a specific alternative model would be a Hausman test (see Hausman 1978), comparing the estimates using ratings as well as choice data (efficient under the null) with the estimates based upon the choice data only (inefficient under the null, consistent under the alternative). A problem with the standard way of performing the test is that the estimated difference of the two covariance matrices is not always positive definite - although it should asymptotically be positive definite under the null. Moreover, the power of this test could be limited. Since we do have particular alternatives in mind here, a more natural way to go is to formulate a more general model which nests the joint model introduced above but has separate utility indexes underlying ratings and choices, and perform a Likelihood Ratio (LR) or a Lagrange multiplier test. We will use the LR test, since the estimates of the more general model are of some interest by themselves, possibly indicating why the joint model is rejected.

A more general model can be formulated as follows. The natural generalisation of the joint model is that the ratings are not generated by (3.8) but by a separate utility index

$$V_{ij} = -\alpha_{i0} + X_j'\alpha_i \tag{3.12}$$

$$\alpha_{ik} = a_k + \eta_{ik}, \quad k=0,\ldots,K. \tag{3.13}$$

Similar assumptions are made on the distribution of $\eta_i = (\eta_{i0},\eta_{i1},\ldots,\eta_{iK})$ as on u_i (but with potentially different parameters). It seems reasonable to allow for an arbitrary correlation coefficient between η_i and u_i. A parsimonious way to achieve this, is the following specification of η_{ik}:

$$\eta_{ik} = \theta_k[\lambda u_{ik} + (1-\lambda)w_{ik}], \tag{3.14}$$

with $w_{ik} \sim N(0,1)$, mutually independent and independent of other error terms and of exogenous variables. If $\lambda=0$ in (3.14) this implies that random coefficients in ratings and choice are independent, and the model partitions into independent models for ratings and choice. Without restrictions on the parameters across the two parts of the model, ML (or simulated ML) estimates for this model with $\lambda=0$ will be the same as ML estimates for separate ratings and choice models. If $\lambda=1$, the η_{ik} are perfectly correlated to the u_{ik}, though they still may have different variances, and the random coefficients may still have different means and variances.

In the general model, two constraints have to be imposed on the ratings part of the model, since scale and location of this part of the model are not identified without imposing restrictions across the ratings and the choice parts. We set $\sigma_v=1$ and $a_0=b_0$. The joint model discussed above results if we impose the restrictions

(3.15) $\lambda=1$, $a_k = b_k$ $(k=0,\ldots,K)$, $\theta_k = 1$ $(k=0,\ldots,K)$.

These are 1+2(K+1) restrictions, but this is partly compensated by the two restrictions needed to identify the general model. Thus the Likelihood Ratio test statistic will, under the null that the joint model is valid, asymptotically follow a chi-squared distribution with 2(K+1)-1 degrees of freedom.

3.4 Empirical analysis

3.4.1 Data

The survey analysed in this study was concerned with the evaluation of hypothetical yoghurt products, a commonly consumed commodity in the market that was studied. Data were collected using a survey distributed to respondents participating in the CentER*data* consumer panel. This panel consists of consumers throughout The Netherlands and has been administered by Tilburg University since 1998. Respondents were screened for regular yoghurt consumption, and of the 977 respondents surveyed, 909 remained after incomplete and incorrect responses were removed.

In the survey, respondents were asked to imagine having lunch in a cafeteria and having to decide whether or not to purchase a 200ml container of yoghurt with their meal. The attributes considered in the survey and their levels are summarised in table 3.1. Attributes and their levels were selected after a thorough examination of yoghurt products in local supermarkets, and discussions with regular yoghurt consumers. A total of 7 attributes, each presented at 2 levels, were used in the presentation of products: 3 continuous variables (price, fruit content, fat content) and 4 binary variables (biological cultures, artificial flavouring, creamy taste, recyclable packaging).

To control for the possible effect of attributes not included in the study, respondents were instructed to assume that the yoghurts were identical with respect to all characteristics not presented in the survey and were available in their favourite flavour. Furthermore, they were advised to assume there were no other yoghurts available in the cafeteria when considering each separate question.

Table 3.1: Attributes and levels used in the experiment

Attribute	Description of levels	Coding in estimation
Price	NLG 1.90	1.9
	NLG 1.50	1.5
Fruit content	10% fruit	10
	5% fruit	5
Biological cultures	Contains biological cultures	1
	Contains no biological cultures	0
Artificial flavouring	Contains artificial flavouring	1
	Contains no artificial flavouring (all natural)	0
Creamy taste	Creamy taste	1
	Regular taste	0
Fat content	0.5% fat content	0.5
	3.5% fat content	3.5
Recyclable packaging	Yoghurt container is recyclable	1
	Yoghurt container not recyclable	0

Statistical design methods, following Louviere and Woodworth (1983), were used to construct product profiles and choice sets in which attributes were orthogonal. To calibrate the attribute levels a small survey was conducted from which preliminary marginal utility contributions were estimated for each attribute. Using this information, the levels of the continuous attributes were adjusted so that the predicted change in utility between the two levels considered was approximately equal to the average change in marginal utility associated with the binary attributes. Maintaining utility balance across attributes is important for improving the efficiency of statistical designs (Huber and Zwerina 1996).

Each participant in the survey was first asked to rate eight yoghurt products and then to complete a series of eight choice questions. Half of the respondents were also given eight hold-out choice questions that were used for further model validity testing (see subsection 3.4.3). The design of the rating and choice tasks is as follows.

Ratings task

With seven attributes each described at two levels, $2^7 = 128$ distinct product profiles can be created, which if all combined in the same survey questionnaire would result in an orthogonal array of attribute levels. The fact that the total number of possible combinations increases so rapidly, has led to increased use of fractional factorial designs (see Green 1974), which greatly reduce the number of product profiles to be presented whilst maintaining orthogonality between the main effects of the attributes. The use of such orthogonal arrays presents one of the major advantages of SP data over RP data, as the latter is often found to exhibit collinearity between attributes, hampering identification of the marginal contribution of different attributes. Using a 1/16 fraction main effects design produced eight mutually orthogonal product profiles.

All subjects were presented with each of the eight product profiles and asked to separately indicate for each product, on a scale of 0 - 100, the probability that they would purchase the yoghurt if there were *no other yoghurts* available in the cafeteria. Probability ratings tend to have a good rationale for predicting choice compared to other forms of ratings data (Elrod et al. 1992, Wittink and Cattin 1989). Moreover, phrasing the question as a probability of purchase makes it reasonable to assume that the rating scores are based upon comparing the utility of each alternative with the utility of the 'none'-option of not buying any yoghurt product. This assumption is made in the modelling section. The same 'none'-option is also incorporated in the SP choice sets (see below).

As explained in the previous section, we do not use the exact ratings on the continuous scale 0 – 100, but first transform them into categorical levels. Since the frequencies in the data show clear peaks at multiples of 10, we used eleven categories: 1 if the rating is less than 10, 2 if the rating is greater than or equal to 10 and less than 20, and so on with category 11 representing ratings of 100.

Choice task

After the eight ratings questions, each respondent answered eight choice questions. In each of these, respondents were asked to choose one option from a hypothetical choice set including yoghurt products and the 'none'-option. The choice sets contained two products, which were again described by bundles of the attributes introduced above. One option in each choice question was constructed based upon the same eight profiles that were used to construct the ratings questions. The other option was its so-called 'foldover' profile, which in the case of binary attributes is the product with the exact opposite attribute levels. This approach guaranteed orthogonality within and between the two yoghurt options in the different choice sets. Moreover, having a constant reference alternative (the 'none'-option) in each choice set guarantees that the choice sets exhibit orthogonality not only in attributes but also in *attribute differences*. Orthogonality in attribute differences is statistically more important than orthogonality in attribute levels for identification of main effects in 'difference-in-utility' models such as the MNL model (Louviere 1994, Louviere and Woodworth 1983).

3.4.2 Estimation Results

Table 3.2 presents the results of the joint model estimated on the ratings questions and the eight choices for each respondent[4]. The means of the random coefficients all have the expected sign and are strongly significant. The confidence intervals for the standard deviations of the random coefficients never contain the value zero, indicating the existence of significant heterogeneity in preferences between respondents.

To test the joint model formally, we also estimated the more general model using (3.12) to (3.14). The estimation results are presented in table 3.3. As in table 3.2, all parameters have the correct sign and are significant at the 5% level. Estimated means of the random coefficients for ratings and choices are of the same order of relative magnitude, with some notable exceptions. In particular, the price effect in the ratings estimates is about 20% larger than in the choice estimates, suggesting that the ratings are more sensitive to price than the choices. Furthermore, 'biological cultures' and 'recyclable packaging' also are relatively larger in the ratings estimates. Most of the estimated standard deviations for ratings and choice parameters are similar in magnitude.

[4] All results are based upon $T=40$ draws in the simulated maximum likelihood procedure for each respondent.

Table 3.2: Estimation results: Joint model

Parameter	*Estimate*	*Standard error*
Mean coefficients		
(β_{i0}) – None Constant	-3.037	0.122
(β_{i1}) – Price	-1.285	0.064
(β_{i2}) – Fruit	0.141	0.005
(β_{i3}) – Biological Cultures	0.412	0.025
(β_{i4}) – Artificial Flavouring	-0.793	0.032
(β_{i5}) – Creamy Taste	0.476	0.025
(β_{i6}) - Fat Content	-0.355	0.011
(β_{i7}) – Recyclable Packaging	0.564	0.026
Standard deviations of Random coefficients		
(ω_0) – None Constant	1.053	0.035
(ω_1) – Price	0.473	0.018
(ω_2) – Fruit	0.076	0.004
(ω_3) – Biological Cultures	0.144	0.029
(ω_4) – Artificial Flavouring	0.727	0.030
(ω_5) – Creamy Taste	0.418	0.029
(ω_6) - Fat Content	0.373	0.011
(ω_7) – Recyclable Packaging	0.071	0.035
Category Thresholds		
m_1	-1.243	0.061
m_2	-0.579	0.048
m_3	0.122	0.037
m_4	0.592	0.035
m_5	1.124	0.037
m_6	2.106	0.048
m_7	2.725	0.060
m_8	3.625	0.079
m_9	4.535	0.101
m_{10}	5.442	0.126
Ratings error standard deviation (σ_v)	1.540	0.042

Table 3.3: Estimation results: General model

	Choice part		*Ratings part*[5]	
Parameter	*Estimate*	*Standard error*	*Estimate*	*Standard error*
Mean coefficients				
(β_{i0}) – None Constant	-3.248	0.167	-	-
(β_{i1}) – Price	-1.186	0.091	-1.402	0.123
(β_{i2}) – Fruit	0.139	0.008	0.133	0.009
(β_{i3}) – Biological Cultures	0.360	0.042	0.477	0.045
(β_{i4}) – Artificial Flavouring	-0.870	0.044	-0.752	0.051
(β_{i5}) – Creamy Taste	0.429	0.038	0.532	0.044
(β_{i6}) – Fat Content	-0.403	0.015	-0.331	0.016
(β_{i7}) – Recyclable Packaging	0.478	0.042	0.694	0.047
Standard deviations of Random coefficients				
(ω_0) – None Constant	1.539	0.075	1.246	0.025
(ω_1) – Price	0.388	0.032	0.238	0.014
(ω_2) – Fruit	0.096	0.007	0.077	0.004
(ω_3) – Biological Cultures	0.053	0.059	0.132	0.043
(ω_4) – Artificial Flavouring	0.767	0.057	0.707	0.042
(ω_5) – Creamy Taste	0.452	0.048	0.309	0.041
(ω_6) - Fat Content	0.392	0.019	0.377	0.011
(ω_7) – Recyclable Packaging	0.003	0.055	0.114	0.046
Category Thresholds				
m_1			-0.935	0.321
m_2			-0.280	0.320
m_3			0.411	0.320
m_4			0.874	0.320
m_5			1.399	0.319
m_6			2.365	0.318
m_7			2.974	0.317
m_8			3.859	0.316
m_9			4.761	0.314
m_{10}			5.659	0.313
λ	0.937	0.023		

[5] For normalization purposes, β_{i0} in the ratings part of the model is set equal to β_{i0} from the choice part.

The estimated value of λ was 0.937 with standard error 0.023. Thus λ is significantly different from zero as well as from 1. (The latter result is also obtained using a Likelihood Ratio test.) The model with λ=0 is the same as the combination of two separate independent models for ratings and choice. Thus the result that λ is significantly different from 0 implies that ratings and choice data cannot be treated as independent samples. The result that the estimate of λ is close to 1 implies that knowledge of a specific respondent's utility function based on their ratings, would also be informative about their choice probabilities. Although the coefficients differ in mean and dispersion, they are strongly correlated. Thus, combining the two data sources can be expected to provide a more stable basis for segmenting consumer populations in terms of their preferences.

Considering the small standard errors, the difference in parameters between ratings and choice can be expected to be significant, suggesting that the joint model will statistically be rejected against the more flexible model. To test this observation formally, a Likelihood Ratio test was conducted comparing the joint model to the general model. This test rejected the null hypothesis that ratings and choice are based upon the same utility indices. Some further tests of hybrid models allowing for more flexibility in the joint model were also conducted. All hybrid models were rejected against the general model. The log-likelihood values of these models and the successive differences are reported in table 3.4.

The fact that ratings and choices are far from independent can also be confirmed in another way. Separate estimations of the choice model and the ratings model (after adding an appropriate normalisation to the latter) give log-likelihood values summing up to -20864.8. This sum is the log-likelihood of a combined model that imposes independence of random coefficients in ratings and choice (λ=0 in (3.13)). According to a Likelihood Ratio test, this model is rejected against the general model. It is interesting to note that the likelihood of the model imposing independence is also much lower than the likelihood of the much more parsimonious joint model. Although the two models are non-nested so that a standard Likelihood Ratio test cannot be performed, this shows that the joint model performs much better than a model imposing independence (although even the joint model is rejected against the general model with dependence).

Table 3.4: Likelihood ratio test results

Model specification	*Likelihood*	*Difference with previous model*	*d.f. difference with previous model*
Joint model	-20607.4	-	-
Standard deviations differ	-20563.2	44.2*	8
Standard deviations and price parameter differ	-20559.4	3.8*	1
Standard deviations and price, biological cultures and recyclable packaging differ	-20544.8	14.6*	2
Standard deviations and all coefficients differ	-20532.6	12.2*	4
Standard deviations and all coefficients differ and λ is estimated	-20530.6	2.0*	1
Independent models for ratings and choice	-20864.8	n.a.	n.a.

* significantly different from the previous (more parsimonious) model at the 95% confidence level

3.4.3 Predictive Tests on Hold-out Choices

Although an efficiency gain is obtained in estimating the parameters of the choice model using the ratings data, the question seems justified whether using the ratings data affects predictions of consumer choice. And if so, if the more parsimonious joint model or even a choice only model might not predict equally well as the flexible general model. We address this question by looking at some predictions for three alternative choice situations. For this purpose, we use the hold out choice questions answered by the respondents.

The difference between the hold-out groups was only in terms of the number of alternatives that were presented in each choice set. For hold-out group 1, the new choice sets are of the same type as the old ones (two products and the 'none'-option). In hold-out group 2, respondents evaluated four alternatives (plus the 'none'-option), none of which was dominated by one of the others. Respondents in hold-out group 3 evaluated choice sets with six non-dominated alternatives and the 'none'-option.

Predictions for the joint and general model are generated in the following way. For each respondent, 20 values of the random coefficients are generated using the estimated parameters. In case of the general model only the choice parameter estimates were used. Based upon these coefficients, the utility values of each of the alternatives in each of the eight new choice situations are predicted. This gives choice probabilities for all the alternatives[6], and we have computed the averages of these probabilities in each hold-out group.

The predicted shares are compared to the actual shares in the hold out data. We have summarised the results in terms of mean absolute deviation, where the mean is taken over the alternatives in each choice set and over the eight choice sets. This is done for the parameter estimates of the choice only model, the joint model and the general model. Results are given in table 3.5.

All models performed quite well. It can be seen that all three models performed very similarly in terms of predictive accuracy, with a small advantage for the joint model. The improvement in predictive performance of the joint model over the choice only model was only small. This was especially so for the two hold-out groups where more alternatives per choice set were evaluated than in the original choice sets.

Table 3.5: Mean absolute deviations from actual choice shares

Hold-out group	*Choice only model*	*Joint model*	*General model*
1 identical choices (n = 147)	0.092	0.071	0.077
2 four alternatives (n = 164)	0.050	0.047	0.051
3 six alternatives (n = 153)	0.044	0.044	0.045

[6] The 'none'-option is treated in the same way as the other alternatives.

3.5 Discussion

Various theoretical approaches can be taken to explain the observed differences in ratings and choice estimates. In reviewing the relevant literature, the more psychologically oriented set of potential explanations can be distinguished from the more economically oriented set. Olsen et al. (1995) give a good review of the former, while Carson et al. (1999) review the latter. The different explanations that are suggested are now briefly reviewed and tested on our findings.

3.5.1 Psychological Explanations

A first possible explanation found within the psychological literature is the *prominence effect* (e.g., Tversky et al. 1988). This effect occurs if the most important piece of information in the description of an alternative receives greater weight in a choice task than in a judgement task such as a rating. The underlying explanation is that in judgement tasks respondents tend to use more compensatory evaluation processes than in choice, taking into account more aspects of the alternatives. As a consequence, choice based estimates would have higher values for the most important attributes. Our results may perhaps be explained in part by this effect. After correcting for coding differences (multiplying with ranges for each attribute), the most important attributes in terms of utility both in the ratings and choice responses were fat content and artificial flavouring (see table 3.6). Although the difference was not large, the relative value of these two parameters compared to all other parameters except for fruit was higher in the choice estimates than in the ratings estimates, providing some support for the prominence effect.

A related explanation that has been suggested is that if judgement tasks lead to more compensatory evaluations (Billings and Scherer 1988, Einhorn et al. 1979) more attributes should be of importance and/or significance in the ratings estimates, while fewer parameters should be so in the choice estimates. This effect occurred only to a minor degree in our findings. All attributes were significant in the estimates for both response types. Also, the relative size of the attributes was largely similar over response modes, possibly with the exception of recyclable packaging, which was relatively more important in the ratings responses (see table 3.6).

Table 3.6: Comparison of ratings and choice based estimates

	Estimate corrected for coding differences		Importance ranking		Relative size*	
Parameters	Choice part	Ratings part	Choice part	Ratings part	Choice part	Ratings part
Price	-0.474	-0.561	4	5	0.13	0.16
Fruit	0.695	0.665	3	4	0.39	0.36
Biological cultures	0.360	0.477	7	7	0.00	0.00
Artificial flavouring	-0.870	-0.752	2	2	0.60	0.53
Creamy Taste	0.439	0.532	5	6	0.08	0.11
Fat content	-1.209	-0.993	1	1	1.00	1.00
Recyclable packaging	0.403	0.694	6	3	0.05	0.42

* Relative size is calculated as $\frac{|\beta_k|-|\beta_{min}|}{|\beta_{max}|-|\beta_{min}|}$, where β_k is the relevant parameter and β_{min} and β_{max} are the parameters with the lowest and highest absolute value respectively (all corrected for coding differences).

A second possible psychological explanation can be found in the *compatibility effect* (e.g., Montgomery et al. 1994). This effect indicates that product information that is presented in a format that is more similar to the response format will receive greater weight in the evaluations. The underlying explanation for the effect is that cognitive switching costs are lower between similar types of information, making it easier to include information that matches with the response task in the evaluation. On the basis of this effect one would expect the attributes price, fruit and fat content to have a greater relative importance in the ratings estimates, while the (dichotomous) other attributes should have greater importance in the choice estimates. This effect is rejected by our results (see table 3.6).

3.5.2 Economic Explanations

The economic literature in this area stresses the potential for *strategic behaviour* on the part of the respondent (Carson et al. 1999). It is assumed that the respondents act rationally in choosing which information they wish to provide to manufacturers. Therefore, different response formats and different assumptions that consumers may make with respect to manufacturers' intentions are expected to lead to different strategic incentives for respondents.

In our study, the two response formats have the following relevant aspects. In the ratings task, consumers are asked to evaluate an alternative over the option of not buying. In the choice task, a comparison is made between two alternatives, while the option of not buying is included also. In both cases, the likely assumptions with respect to the manufacturer's intentions that consumers may make are that on the basis of the consumer's responses the manufacturer may: 1. Decide on the optimal price and promotions level to set for its yoghurt products, and 2. Decide on whether or not to introduce a new yoghurt product in the market, and if so, which new products to introduce.

In response, the rational consumer will choose an answering strategy that strategically speaking should lead to lower manufacturer pricing and more new product introductions, especially introduction of products that are liked by the consumer. This behaviour is rational because it reduces consumer costs and increases the number of consumer choice options at no additional cost.

To achieve this type of desirable manufacturer response, the strategically optimal consumer response strategy differs for the two response formats. In the ratings responses, consumers should indicate a relatively low willingness to pay for existing products and a relatively high willingness to pay for new products. Note that this strategy is not in line with revealing the consumer's true preferences for different attributes. In particular, the observed price sensitivity can be expected to be higher than the consumer's true price sensitivity (leading to lower manufacturer pricing), and the consumer's utility for new product features can be expected to be higher than the consumer's true utility (leading to more new product introductions). In the case of choice responses, the strategically optimal consumer response is more aligned with responding according to their actual preference. If in comparing the two alternatives, the consumer makes the assumption that only one of the alternatives will be introduced in the market, it is in the consumer's interest that only his or her most preferred product is introduced. Therefore, in the trade off between the two products it is in the consumer's interest to reveal their true preference and price sensitivity. In the comparison with the 'none'-option, similar considerations exist as in the ratings task, so that even the choice based estimates may not be fully in line with the consumer preferences.

Based on the differences in strategic incentives between the two response formats, one would expect to find higher price sensitivity in the ratings task and higher utility estimates for possible new attributes in the ratings task. Because the attributes biological cultures and recyclable packaging currently are not offered in most cafeterias, consumers could regard these as possible product innovations. Thus it can be expected that these attributes should receive relatively higher utility estimates in the ratings parameters. These expectations are supported by our results. The relative size of the price parameter and the estimate for recyclable packaging are higher for the ratings responses, thus providing support for the economic explanation. Because the parameter for biological cultures was used as a minimum benchmark for both response types, its relative size could not be established.

3.6 Conclusion

We have developed a model to combine and compare consumer utility estimates based on stated preference ratings and choice responses. The modelling approach combined two components: a random coefficients ordered probit to model consumers' rating responses and a random coefficients logit to model consumers' choices. Correlation between the two components was introduced through the random coefficients in the model. An empirical application of the proposed model illustrated its flexibility in comparing and combining parameter estimates based on consumer ratings and choice data.

In our empirical results we found significant differences between ratings based and choice based utility estimates. In particular, respondents were relatively more price sensitive in the ratings tasks as well as more positive about possible new product extensions (i.e., recyclable packaging). These observed effects were in line with possible strategic behaviour by consumers in responding to the survey questions. Some support was found also for the prominence effect indicating that the most important attribute received greater weight in the choice task. No support was found for the compatibility effect.

Despite these differences in parameters it was found that the predictive ability of the different models was very similar. This finding may seem surprising, but is in line with earlier results by Dawes (1979) who showed that linear models perform very well in predicting the outcome of choice tasks even if the linear models are only directionally correct and the parameter values have incorrect values. Empirical results by Elrod et al. (1992) also illustrate a similar predictive ability of different model specifications based on consumer ratings and choice responses, further supporting the view that aggregate predictions are robust over utility measurement approaches.

Given that strategic response behaviour can explain part of the observed differences between ratings and choices in our estimates and the fact that choice tasks are less prone to strategic respondent behaviour, the results suggest that choice responses may be more suitable if one wishes to understand consumer preference structures. Carefully designed choice experiments can be used to avoid potential biases due to strategic behaviour. Further research in this area could explore consumers' inclinations to respond strategically under different conditions (e.g., by changing the context presented in the study). Based on our findings future research also may address the possible value of combining ratings and choice responses in consumer segmentation research. For example, segmentation may be more successful if one takes into account the correlation in individuals' ratings and choice responses. The cost efficiency of collecting these two types of responses simultaneously may also be studied, trading off the costs of additional data collection per respondent against the costs of collecting data from more respondents. If the prediction of market shares is the objective however, collecting data in one response format may be equally suitable.

Appendix

3.A Smooth Simulated Maximum Likelihood

To estimate the joint model[7] by simulated ML, the multi-dimensional integral in the unconditional likelihood is approximated by a simulated mean. This simulated mean is based upon draws of standard normal error terms which can be transformed into β_{i0} and β_i. Let T denote the number of independent draws of all random variables that will be used per individual. T has to be chosen prior to estimation. Smooth simulated ML is then based upon the following steps:

1. Before starting the ML algorithm, draw (K+1)NT independent standard normal variables ζ_{ikt}
2. During a specific ML iteration, for given values of the parameters, the means and variances of β_{i0} and β_i are given by b_k, and ω_k^2 (k=0,..,K; i=1,…,N). Now set $\beta_{ikt} = b_k + \omega_k\zeta_{ikt}$. Thus the β_{ikt} can be seen as independent draws from $N(b_{ik,}, \omega_k^2)$, the correct distribution of the random variables β_{i0} and β_i which should be drawn). Stack them into (K+1)N vectors of length T: $\beta_{i1}=(\beta_{i01},\ldots,\beta_{iKt})'$.
3. Instead of maximising $\Sigma_i \log L_i$, maximise $\Sigma_i \log LS_i$, where: $LS_i = 1/T\sum_{t=1}^{T} L_i(\beta_{it})$. Thus the expected value is replaced by a simulated sample mean of T draws. The Law of Large Numbers implies that for large T, LS_i will approximate L_i.

It can be shown that this procedure is asymptotically equivalent to maximum likelihood provided that $T\to\infty$ fast enough (e.g., Hajivassiliou and Ruud 1994). This implies that standard ways of obtaining ML estimates, standard errors, etc. can be used. The approximated likelihood $\Sigma_i \log LS_i$ can be treated as the real likelihood. Since the ε_{ijs} in (3.5) and the v_{ij} in (3.8) are not simulated, the simulated likelihood function is a smooth (differentiable) function of the parameters to be estimated. This has several advantages over some of the early, non-smooth, simulated maximum likelihood methods (see Hajivassiliou and Ruud 1994).

[7] The other models can be estimated in a similar way.

Chapter 4

Optimal Effort in Consumer Choice

This paper develops a theoretical model of optimal effort in consumer choice. The model extends previous consumer choice models in that the consumer not only chooses a product, but first decides how much effort to apply to a given choice problem. Rather than considering only the payoff of the chosen outcome, the consumer's objective function also contains the costs of cognitive effort. In our model, the optimal level of effort is based on the consumer's cost of effort, the expected utility gain of a correct choice and the complexity of the choice set. To explore the empirical validity of the model, a survey of hypothetical consumer restaurant choices was conducted. Response time was measured as a proxy for effort, while consumer involvement measures were taken as proxies for individual differences in cost of effort and perceived complexity. Response time on each choice question is explained by the respondent specific consumer involvement measures, and two choice task specific variables: the (estimated) utility difference between alternatives, and the number of elementary information processes (EIP's) of the choice problem. The findings are consistent with the theoretical model. For example, response time is found to increase with the consumer's interest and pleasure, which is in line with the notion that for very interested consumers, the cost of effort (compared to the expected utility gain of a correct choice) will be low. Effort is found to increase with both the utility difference and task complexity.

4.1 Introduction

Economic models of choice have traditionally been developed under the assumption that consumers are rational utility maximisers. This assumption has been popular in consumer choice modelling because in the random utility theory framework, it provides tractable estimable models of consumer choice (e.g., McFadden 1986). In these models, observed inconsistencies in choice behaviour, or "errors", are typically taken to be the result of observational deficiencies on the part of the analyst (Ben-Akiva and Lerman 1985). The traditional model presumes that decision-makers have the skills that are necessary to make whatever complicated calculations are required to discover the optimal product, with the implication that neither complexity nor consumer effort should play a role in the consumer decision.

More behaviourally oriented research on consumer decision-making on the other hand tends to acknowledge that consumers do not always behave in a perfectly rational manner. In particular, consumers have been found to employ simplifying strategies to reduce cognitive requirements (Bettman et al. 1993a,b) and to vary in the accuracy with which they make their choices (Haaijer et al. 2000) and provide preference evaluations (Fischer et al. 2000). In response, it has been proposed that consumers should be modelled as being boundedly rational (see Rubinstein 1998 for a recent review).

An approach to consumer rationality that recognises the constraints on the decision process arising from the limitations of human beings as problem solvers with limited information-processing capabilities, is to assume that consumers rationally take into account their limitations when making their decisions (Tversky 1969, Johnson and Payne 1985). Thus, rather than considering only the payoff of the chosen outcome, the consumer's objective function may also contain the costs of the effort required for making the choice. This is the approach taken in this chapter: we develop a model in which effort is required to acquire information and thus reduce the probability of a sub-optimal choice. Effort comes at a cost, and thus the consumer makes a trade-off between the costs of effort and the expected utility loss due to sub-optimal choice. Our focus is on explaining how much effort consumers put into choosing between two products if they rationally include the cost of effort in their objective function. We allow the choice of effort to depend on the expected payoff from a correct choice (the utility difference between the products), the complexity of the choice problem, and the cost of effort. Behavioural implications of the theoretical model are analysed to provide insight into how choices are affected by shifts in the model's parameters. We show that the model can explain various well-accepted empirical relationships between effort and choice set and consumer characteristics. It provides a unifying framework in which these relationships are not only identified but also explained as the result of optimising behaviour.

We explore the validity of this model with an empirical analysis. In a survey of consumers' hypothetical restaurant choices, response time was used as a proxy for the effort consumers put into their decision. Consumer involvement measures were taken as proxies for individuals' cost of effort and perceived complexity. Furthermore, choice sets were varied in composition to allow for an analysis of the impact of product utility differences and choice set task complexity on effort. Least squares regressions are used to explain response time from the consumer involvement measures and from the product utility difference and choice task complexity. Results are found to be consistent with the behaviour implied by the theoretical model. They imply that effort decreases with the cost of effort and with product utility difference, and both perceived and objectively measured choice complexity.

The remainder of the chapter is organised as follows. In section 4.2 we discuss the components of our model and their relation to the existing literature. The economic model is presented in section 4.3. Section 4.4 discusses our empirical analysis and section 4.5 concludes the chapter.

4.2 Effort and Consumer Choice

In this section we first discuss the issue of how to measure choice effort in consumer decision making. Next, we discuss how differences in effort between choices can be related to differences in costs of effort, product utility differences and perceived choice set complexity. We also discuss previous research relating consumer involvement to consumer decision effort.

Measuring choice effort

Choice effort cannot be measured directly and recourse to a proxy variable is required for any empirical investigations. The proxy most commonly used in previous research is response time (e.g., Haaijer et al. 2000). In the literature on response times, distinctions have been made between various components of the time required to make a choice. For example, Stone (1960) considers the existence of three distinct parts: *input* time, *decision* time and *motor* time. During the period referred to as input time, the information in the choice set is processed. This is then followed by the decision stage where the information is used to identify the preferred alternative. The motor time refers to the time taken to actually make the choice. In the current analysis, we are interested in obtaining an indicator of the level of cognitive processing time preceding the choice as a proxy for effort. The relevant components of total time are thus the input time and the decision time. As discussed in Haaijer et al. (2000), motor time is only a very minor part of total response time. We ignore motor time and assume that response time is approximately the sum of the time required for processing information and identification of the optimal good. Thus for our purposes response time is considered to be measuring the amount of time spent on cognitive processing which is increasing with the level of mental effort.

In previous research, several choice set and individual characteristics have been demonstrated empirically to influence the effort consumers put into the decision making process. In psychology, several researchers have analysed response time and its determinants (e.g., Busemeyer and Townsend 1993, Link 1975, Pollay 1970a,b, Sergent and Takane 1987, Takane and Sergent 1983). These studies yield several proposed antecedents of response times, including choice set structure, choice complexity, and situational and personal influences (Tyebjee 1979). Also recognised are the opportunity costs of processing time (Busemeyer and Townsend 1993, Payne et al. 1992, Shugan 1980). Researchers in marketing have also considered response latencies as providing useful information about the consumer's choice of decision process (see Hutchison et al. 1994, Shugan 1980, Tyebjee 1979, Haaijer et al. 2000).

The effects of cost of effort and product utility difference

When effort is costless the goal of the utility maximising consumer will be to choose the best good no matter how difficult the choice may be. If effort is costly, however, choices may be made on the basis of a more limited type of comparison and personal characteristics may have an impact on the quality of the decision process. Consumers who are more interested in the product category may have lower cognitive costs per unit of effort when comparing products. As a consequence, they may spend more effort on their decision leading to more accurate choices. For example, Mittal and Lee (1989) observed that more involved consumers use more information and go through more brand comparisons when choosing a product.

Similar differences in consumer choice effort can arise from differences in expected product utility differences. The effect of such differences on choice effort is twofold. First, the utility difference between two products affects the pay-off of consumer choice effort directly. Putting effort into choosing between an excellent alternative and a poor alternative has a higher pay-off than applying effort to choose between two alternatives that differ by only a little in utility terms. This would lead to a positive relation between utility difference and effort. On the other hand, the returns to effort in the sense of how much the probability of correct choice increases with an additional unit of effort, will typically depend negatively on the utility difference. When two goods differ a lot in utility terms and the choice is already relatively obvious, additional effort will have very little payoff. This may explain why it has been found that the time taken to compare two goods is inversely related to the difference in utility between the alternatives (Bettman et al. 1993a, Bockenholt et al. 1991, Espinoza-Varas and Watson 1994, Tyebjee 1979). The basic premise is that the closer the alternatives are in terms of utility, the more conflict a choice evokes, requiring deeper analysis by the decision-maker.[1]

[1] As in most past research, conflict here refers to between-alternative conflict, which results if two competing alternatives have a small difference in utility terms (e.g., Shugan 1980). This differs from the approach of Fischer et al. (2000), where a distinction is made between conflict between and within alternatives. The latter is relevant for scenarios where single products are rated individually, rather than for the choice scenarios that we consider.

Choice task complexity

Choice task complexity may affect the decision process used in a particular choice situation (Bettman et al 1993b, Bettman et al. 1990, Espinoza-Varas and Watson 1994, Hendrick et al. 1968, Pollay 1970a,b, Shugan 1980, Swait and Adamowicz 2000, Tyebjee 1979). Differing levels of task complexity could induce the decision-maker to vary the decision process in two ways. First, as complexity varies, the individual may utilise the same decision strategy but may vary the amount of effort spent on it. For example, as complexity changes, a consumer using a compensatory choice process might vary the amount of effort spent evaluating each attribute. Secondly, the decision-maker may switch to a different decision strategy altogether. This would occur if the consumer used for example a compensatory choice process in one choice environment and a lexicographic method in another. However, in whichever way consumers respond to increases in complexity, a common finding in the literature is that effort has an inverted U-shaped relationship with complexity (Hendrick, et al. 1968, Kiesler 1966, Pollay 1970a,b, Swait and Adamowicz 2000). That is, initially, effort or decision-time increases with difficulty up until a point where the decision becomes too difficult and effort decreases again.

Research in behavioural decision theory has suggested several aspects of choice sets that have the potential to increase the effort required for choosing the product with the highest utility (e.g., Bettman et al. 1993a). The number of alternatives and the number of attributes describing the alternatives are found to be key drivers of this effort. One approach to incorporate these and other cognitive processing influences on complexity, is to count the number of elementary information processes (EIP's) required for performing the choice task. This idea of decomposing choice strategies into a set of components has been suggested for example by Huber (1980) and Johnson (1979), and was implemented in a set of Monte Carlo experiments by Johnson and Payne (1985). These studies draw on ideas of Newell and Simon (1972) who suggested that heuristic strategies could be constructed from a small set of elementary information processes. Examples of EIP's suggested by Newell and Simon are 'READ' (read an alternative's value for a specific attribute), 'COMPARE' (compare two alternatives on an attribute), 'ADD' (add the utility values of different attributes), etc. In previous research, it was emphasised that EIP's depend on the nature of the choice problem as well as the decision strategy. For example, Johnson and Payne (1985) compare the number of EIP's required by different decision processes for a fixed choice task (i.e., keeping complexity constant) and find that more accurate decision strategies typically require a greater number of EIP's. We will use EIP's as a measure of choice set complexity, keeping the decision strategy constant.

Consumer Involvement

In our empirical analysis, we employ consumer involvement measures to explain how consumers may differ in terms of cost of effort or perceived choice set complexity. The consumer involvement construct is well known in the marketing literature and has received a broad range of definitions. It appears to be multidimensional and multifaceted in nature; see the comprehensive reviews and discussions in Andrews et al. (1990) and Poiesz and De Bont (1995). In spite of the lack of an unambiguous definition of the term, involvement has long been considered to be a crucial determinant of consumer choice behaviour. More involved consumers are more willing to process information about the product characteristics and marketing strategies (Andrews et al. 1990, Celsi and Olsen 1988). They use a more compensatory choice process (Gensch and Javalgi 1987). They have a higher awareness of product features through greater pre-purchase search effort (Beatty and Smith 1987, Bloch et al. 1986, Clark and Belk 1979, Moore and Lehmann 1980), as well as increased levels of ongoing search (Bloch et al. 1986, Bloch and Richins 1983). More involved consumers use more information and more brand comparisons (Mittal and Lee 1989), have greater attention (Pratkanis and Greenwald 1993), and apply more cognitive effort (Petty and Cacioppo 1986).

A major theme in this literature is that further empirical work is needed to test the various theories of involvement. However, with the availability of so many definitions the researcher is left in a quandary as to which particular usage to apply. Depending on the various antecedents of involvement, consequences for consumer behaviour may differ. The effect of involvement on response time is better captured when all its antecedent facets are considered. We therefore investigate the influence of involvement on consumer behaviour using the Consumer Involvement Profile (CIP) developed by Laurent and Kapferer (1985). This explicitly identifies specific components of involvement. Moreover, in many studies, the CIP construct was generally found to be consistent and reliable across different applications and contexts (Rodgers and Schneider 1993, Dimanche et al. 1991, Goldsmith and Emmert 1991, Mittal 1995, Celuch and Evans 1989). The CIP scale distinguishes five potential components of consumer involvement: the level of product interest, the level of pleasure the consumer derives from the product, the product's sign or symbolic value to the consumer, the importance the consumer assigns to making the wrong choice, and the probability the consumer assigns to making the wrong choice. How we expect these components to be related to choice effort is discussed in section 4.4 where we propose relationships between consumer involvement, perceived complexity and the cost of effort. First, we introduce the theoretical model underlying these expectations in section 4.3.

4.3. A Model for Optimal Effort in Discrete Static Choice

This section presents a model that describes the behaviour of a utility maximising consumer whose choice of how much effort to apply to a particular choice problem depends upon personal characteristics and choice set characteristics. Firstly, the theoretical model is described (subsection 4.3.1). In subsection 4.3.2, we present the comparative statics for the general model, and analyse how optimal effort changes with the relative cost of effort, with choice complexity, and with the utility difference. It appears that we cannot draw unambiguous conclusions on the directions of the effects of changes in complexity or utility difference on the optimal effort level. We therefore add specific distributional and functional form assumptions, and numerically analyse how effort changes with cost of effort, complexity, and utility difference for this special case (subsection 4.3.3).

4.3.1 The Model

The model explains two things: how much effort does a consumer apply to acquire information relevant to the choice decision, and which choice does he make. In practice, these decisions will be intertwined: some effort is applied, some information is collected; this is used to decide whether or not more effort will be applied, etc. Such an iterative model would be hard to formalise and impossible to validate with existing data. Instead, we work with a stylised non-iterative model in which, based upon a prior, effort is decided upon, then products are evaluated and the choice is made.

The model considers a consumer faced with a choice between two products, say 0 and 1, with utilities U_0 and U_1. We assume that the consumer's decision process consists of several stages:

1) The consumer takes a first glance at the two alternatives. On the basis of this, he constructs some prior distribution of $U_0 - U_1$.

2) On the basis of the prior distribution, the complexity of the choice problem, and the costs of effort, the consumer chooses the optimal effort level for evaluating the two alternatives.

3) The consumer puts effort in evaluating the two alternatives, leading to proxies U_0^* and U_1^* of U_0 and U_1, respectively.

4) The consumer chooses on the basis of U_0^* and U_1^*: Product 0 is chosen if and only if $U_0^* > U_1^*$.

Stage 1: Prior distribution

We can give this the following interpretation. The consumer considers the utility values of the two goods as random draws from some population of utilities (or goods). A global glance at the question gives the consumer some idea about the distribution of the values from which the two utilities are drawn, such as its dispersion. In order to choose between the two products, the consumer will then put effort into studying the two products more carefully. Thus we can say that, before studying the alternatives in detail, the consumer has some (subjective) prior distribution in mind for the utility values U_0 and U_1. The consumer, *a priori*, has no idea which of the two is better. Thus the prior satisfies

(4.1) $$E\{U_1 - U_0\} = 0.$$

We define the expected absolute difference in utility between the two goods D by

(4.2) $$D = E\{|U_1 - U_0|\} = E\{U_{sup} - U_{inf}\}.$$

Here $U_{sup} = \max(U_0,U_1)$ and $U_{inf} = \min(U_0,U_1)$. If D increases, the expected payoff of correctly choosing the superior good over the inferior good will increase. If, for example, the respondent sees at first glance that all attributes are very similar for the two goods, D will be small.

The standardised prior for the consumer is given by:

$$Z = \frac{(U_1 - U_0)}{D},$$

Thus $E\{Z\} = 0$ and, by construction, $E\{|Z|\} = 1$. We will assume that Z has a symmetric continuous distribution:

(4.3) Z has density g(z), which is symmetric around 0.

In the comparative statics and the empirical analysis below, we will assume that the distribution of Z is the same for all consumers and choice situations, implying that D is a scale parameter of the prior distribution of $U_1 - U_0$.

Effort and Utility Proxies

Before making a choice, the respondent puts a certain amount of effort into studying the two products. In this way he obtains proxies U_1^* and U_0^* of the utilities U_1 and U_0. The accuracy a(E;C) of these proxies depends on the level of effort E and on the complexity of the choice C:

(4.4)
$$U_1^* = U_1 + \frac{\varepsilon_1}{a(E;C)}$$

$$U_0^* = U_0 + \frac{\varepsilon_0}{a(E;C)}.$$

where

(4.5) $\varepsilon_0, \varepsilon_1$ are iid with mean zero, independent of U_0, U_1, and Z,

a(E;C) is a scale parameter of $\varepsilon_0, \varepsilon_1$ reflecting "accuracy".

A semicolon is used to distinguish between, E, chosen by the decision-maker, and the exogenous variables (in this case C). This notation is used throughout the remainder of the chapter. The value of a(E;C) determines the importance of the errors, ε_1 and ε_0, in the formation of the proxies U_1^* and U_0^*. The value of this scale parameter is inversely related to the variance of the errors. Thus if a(E;C) increases, the consumers' proxies move closer to the true utility values of the goods, U_1 and U_0.

We will assume:

$$(4.6) \qquad \frac{\partial a(E;C)}{\partial E} > 0 \text{ and } \frac{\partial a(E;C)}{\partial C} < 0 .$$

The function a(E;C) is where effort enters the analysis and is really the essence of the model. An increase in effort by the decision-maker, will lead to an increase in the accuracy of the utility proxies. We do not explicitly specify which choice strategy the consumer uses. Thus an increase in effort may mean that the consumer spends more time evaluating each attribute of each alternative, or (in a non-compensatory strategy) that the consumer evaluates more attributes. This could also mean that the consumer changes from a less effort-intensive to a more effort-intensive decision strategy. According to Johnson and Payne (1985), there appears to be a strong positive relationship between the effort required and expected accuracy across different decision processes, keeping constant the complexity C of the choice problem.

The negative sign for the first derivative of a(E;C) with respect to complexity implies that complexity increases the variance of the error terms, making it more difficult to distinguish the superior from the inferior good. As complexity increases the decision-maker's proxies for the true utilities U_1 and U_0 become less reliable. Thus in a more complex situation, more effort must be applied to achieve the same level of certainty as in a less complex choice. We will assume that the accuracy function satisfies

$$(4.7) \qquad \text{"non-increasing returns to effort":} \quad \frac{\partial^2 a(E;C)}{\partial E^2} \leq 0 \qquad \text{(NIRE)}$$

We will need this condition below to guarantee that the second order condition for optimality of effort is satisfied. It implies that the marginal increase in accuracy from an additional unit of effort falls with each additional unit of effort invested.

Effort and expected utility

Given the proxies U_1* and U_0*, the choice between the two products will be based upon the difference U_1* - U_0*. With the symmetric set up, the optimal choice rule (Stage 4) will be:

Choose 1 if $U_1^* > U_0^*$; choose 0 otherwise.

The expected pay-off or return from the choice is given by

$$E\{1(U_1^* > U_0^*)U_1 + 1(U_0^* > U_1^*)U_0\}.$$

Due to the law of iterated expectations, this can be rewritten as

$$E\{P(U_1^* > U_0^* | U_0, U_1)U_1 + P(U_0^* > U_1^* | U_0, U_1)U_0\},$$

where the expectation is taken over U_0 and U_1. Working out the inner part of this for both $U_0 > U_1$ and $U_1 > U_0$ gives

$$E\{P(\text{correct choice}| U_0, U_1)U_{\sup} + P(\text{incorrect choice}| U_0, U_1)U_{\inf}\}.$$

Or, equivalently

$$E\{U_{\inf} + P(\text{correct choice}| U_0, U_1)| U_1 - U_0 |\},$$

which, due to symmetry of $\varepsilon_0 - \varepsilon_1$ and Z, is the same as

$$E\{U_{\inf}\} + E\{P(\varepsilon_0 - \varepsilon_1 > U_0 - U_1| U_0, U_1) \times | U_1 - U_0 | | U_1 > U_0\}.$$

With $Z = \dfrac{(U_1 - U_0)}{D}$, this becomes

$$E\{U_{\inf}\} + E\{P(\varepsilon_0 - \varepsilon_1 > -D | Z | a(E;C)| Z) \times D | Z |\}.$$

Thus we have shown that the expected return (R) is given by

$$R(a(E;C); D) = E\{U_{\inf}\} + E\{P(\varepsilon_0 - \varepsilon_1 > -D | Z | a(E;C) | Z) \times D | Z |\}. \tag{4.8}$$

Defining $\varepsilon = \varepsilon_0 - \varepsilon_1$, equation (4.8) becomes

$$R(a(E;C); D) = E\{U_{\inf}\} + E\{P(\varepsilon > -D | Z | a(E;C) | Z) \times D | Z |\}. \tag{4.9}$$

The assumption that ε_0 and ε_1 are iid implies that ε is symmetric around zero. In addition, it seems plausible to assume that ε is unimodal, and thus has unique mode at 0. For convenience, we will also assume that ε has a continuous distribution with differentiable density f_ε. These assumptions together imply.

(4.10) $\qquad f_\varepsilon'(x) > 0$ for $x < 0$ and $f_\varepsilon'(x) < 0$ for $x > 0$. (USYM)

Together with the non-increasing returns to effort assumption in (4.7), condition (4.10) will be sufficient to guarantee that the second-order condition for a unique maximum (see (4.14) below) is satisfied.

Optimal choice of effort level E (Stage 2)

Equation (4.9) gives the expected return from the choice in utility terms, given the parameters D and C, and given the effort level E. If effort had no cost, individuals could apply a large level of effort to minimise the probability of choosing the inferior product. This would capture behaviour of a perfectly rational individual (see section 4.2) who optimises perfectly. As mentioned in section 4.2, we assume in the current work that consumers are boundedly rational and have the ability to optimise, but this requires effort which comes at a cost. Cost considerations are introduced into our model by assuming there is a fixed marginal disutility, γ, per unit of effort.

Thus, for a given choice question, the consumer has to decide on the effort level E, knowing γ, D, C, the distributions of Z and ε, and the function a(E;C). The choice of E will be based on the expected return minus the cost of effort, i.e., the consumer solves the problem

(4.11) $$\mathrm{Max}_{E>0} \qquad R(a(E;C), D) - \gamma E.$$

The term $E\{U_{inf}\}$ in (4.9) does not depend on E and can be removed, so that the maximisation problem is equivalent to

(4.12) $$\mathrm{Max}_{E>0} \qquad E\{P(\varepsilon > -D \mid Z \mid a(E;C) \mid Z) \times D \mid Z \mid\} - \gamma E.$$

The optimal level of effort will satisfy the first order condition

(4.13) $$\gamma = \frac{d}{dE}\left[E\{P(\varepsilon > -D \mid Z \mid a(E;C) \mid Z) \times D \mid Z \mid\}\right] \qquad \text{(FOC)}.$$

This simply states that the individual equates the marginal benefits (in utility units) of an increase in R with the marginal cost (in utility units) of effort.

The second order condition required to ensure that the solution to (4.13) is a utility maximum is

(4.14) $$\frac{d^2}{dE^2}\left[E\{P(\varepsilon > -D \mid Z \mid a(E;C) \mid Z) \times D \mid Z \mid\}\right] < 0 \quad \text{(SOC)}.$$

In words, this means that the marginal revenues of effort must decrease with effort. In Appendix 3.A, it is shown that (4.14) will hold if both (4.7) and (4.10) are satisfied.

4.3.2 Comparative Statics: General Case

We now examine how shifts in the model parameters affect the optimal level of effort. The first order condition (4.13) can be rewritten as

$$\gamma = E\left\{\frac{d}{dE}\left(P(\varepsilon > -D \mid Z \mid a(E;C) \mid Z) \times D \mid Z \mid\right)\right\}$$

$$= E\left\{f_\varepsilon(-D \mid Z \mid a(E;C)) \times (D \mid Z \mid)^2 \times \frac{\partial a}{\partial E}\right\},$$

or, in other words,

(4.15) $$\gamma = E\left\{f_\varepsilon(-D \mid Z \mid a(E;C)) \times (D \mid Z \mid)^2\right\} \times \frac{\partial a}{\partial E}.$$

The left-hand side gives marginal costs (MC) of effort (in utility units), the right hand side gives the marginal revenues (MR).

Comparative statics with respect to γ

An increase in γ implies an increase in MC. To restore the equality, MR must rise as well. Due to SOC, this means that E will fall. Thus we have:

$$\frac{\partial E}{\partial \gamma} < 0.$$

An increase in the cost of effort leads to a fall in the optimal level of effort.

Comparative statics with respect to C

The complexity of the choice problem affects MR in two ways:

C1 (*Effect of Accuracy on Probability of correct choice*) If C increases, a(E;C) will fall, and due to (4.10), $f_\varepsilon(-D|Z|a(E;C))$ will rise. This implies that the marginal effect of a change in a(E;C) on the probability of a correct choice will rise, so that the marginal impact of E on the probability of correct choice will rise. This increases MR and thus (due to SOC) increases the optimal level of E.

C2 (*Effect of Effort on Accuracy*) On the other hand, an increase in C will also affect the sensitivity of a(E,C) for E, that is, $\frac{\partial a}{\partial E}$. This effect will depend on sign of the cross derivative $\frac{\partial^2 a}{\partial E \partial C}$. Both signs are possible. With the plausible functional form discussed in the next subsection, we get

Assumption REDC: $\frac{\partial^2 a}{\partial E \partial C} < 0$: returns to effort decrease with complexity.

However the sign could also be positive:

Assumption REIC: $\frac{\partial^2 a}{\partial E \partial C} > 0$: returns to effort increase with complexity.

Under REDC an increase in C leads to a fall in $\frac{\partial a}{\partial E}$ and a fall in MR and the optimal effort level. Thus effects C1 and C2 have opposite signs and the net effect of complexity on MR and E will depend on which of the two dominates. If C1 dominates, E will increase with C; if C2 dominates, E will decrease with C. Since in general, we cannot say which of the two is the case, we have

$\frac{\partial E}{\partial C}$ is not unambiguously determined under REDC.

On the other hand, if REIC holds, the sign of C2 is the same as the sign of C1, and the overall effect of an increase in C is an increase in MR and E. Thus we have

$\frac{\partial E}{\partial C} > 0$ under REIC.

Comparative statics with respect to D

A change in D affects MR in two ways:

D1 (*Effect of accuracy on the probability of correct choice*) if D increases, due to (4.10), $f_\varepsilon[-D|Z|a(E;C)]$ will fall. This reduces MR and thus E is reduced to restore the equality MR=MC (this is similar to C1 above).

D2 (*Direct effect*) if D increases, $(D|Z|)^2$ rises: there is more to be gained by changing the probability of correct choice, due to the larger expected utility difference. Thus MR increases and E increases.

The total effect of the expected utility difference on the optimal effort level is ambiguous.

A change in D versus a change in γ

In our framework, a change in what we have called the utility difference D, affects both the utility gain (leading to D2) and the probability of correct choice (leading to D1), keeping accuracy constant. This may lead to some confusion. For example, a change in preferences will have a direct effect (D2), without affecting the probability of correct choice. In our framework, such a change can be captured not through D, but through a change in the cost of effort γ in the opposite direction: increasing the pay-off to a correct choice (without changing the probability of correct choice) has the same effect on effort as reducing the cost of effort, since the (joint) scale of utility and costs is irrelevant. This has to be kept in mind when discussing how consumer involvement affects the parameters γ, D or C, as we will see below.

4.3.3 A Parametric Specification

The comparative statics derived in the previous subsection do not lead to unambiguous conclusions on how the expected utility difference D and choice complexity C affect the optimal level of effort. In this subsection, we analyse the same relationships for more specific model assumptions, taking a plausible functional form for a(E,C) and assuming normality of the random variables $\varepsilon_1 - \varepsilon_0$ and Z. Specifically, we assume[2]

$$(4.16) \qquad \varepsilon = \varepsilon_1 - \varepsilon_0 \sim N(0,1),$$

$$\text{and} \qquad Z \sim N(0, \pi/2).$$

The variance of $\pi/2$ is chosen so that Z satisfies the condition $E\{|Z|\} = 1$. These assumptions imply (4.10), one of the conditions needed for the second order condition.

We specify the accuracy function a(E;C) as[3]

$$(4.17) \qquad a(E;C) = \frac{E}{C} \qquad \text{for } E, C > 0.$$

This specification satisfies (4.6):

$$(4.18) \qquad \frac{d\,a(E;C)}{d\,E} = \frac{1}{C} > 0 \qquad \text{and} \qquad \frac{d\,a(E;C)}{d\,C} = -\frac{E}{C^2} < 0\,.$$

It also satisfies (4.7), which, together with (4.10), is needed for the second order condition:

$$(4.19) \qquad \frac{d^2\,a(E;C)}{d\,E^2} = \frac{d}{d\,E}\left[\frac{1}{C}\right] = 0 \leq 0\,.$$

Moreover, this choice of a(E;C) implies that returns of effort decrease with complexity:

$$(4.20) \qquad \frac{\partial^2 a(E;C)}{\partial E \partial C} = -\frac{1}{C^2} < 0 \qquad \text{(REDC)}.$$

With these assumptions it can be shown (see Appendix 4.B) that the consumer maximisation problem can be expressed as

$$(4.21) \qquad \mathrm{Max}_{E>0} \qquad \sqrt{2\pi}\, D \iint 1[z_1 > 0, z_2 > 0] z_2 f(z_1, z_2) dz_1 dz_2 - \gamma E,$$

where $f(z_1,z_2)$ is the density of the bivariate normal distribution with means (0,0), variances (1,1) and correlation coefficient

$$(4.22) \qquad \rho = \frac{D\,a(E;C)\sqrt{\pi/2}}{\sqrt{1 + (D\,a(E;C))^2\, \pi/2}}\,.$$

---

[2] The qualitative results do not change if $\varepsilon \sim N(0, \sigma^2)$ with $\sigma^2 \neq 1$.

[3] The qualitative results do not change if $a(E,C) = k\, E^{\alpha}/C^{\beta}$ for $k > 0$, $0 < \alpha \leq 1$, $\beta > 0$.

The function $1[.,.]$ in (4.19) is an indicator function that takes the value unity if both conditions in the square brackets are satisfied, and zero otherwise.

Comparative statics

The model can be analysed numerically to derive the partial relationships between the optimal level of effort and the parameters γ, C, and D. The optimal level of effort can be calculated for specific values of the model parameters γ, C, and D. The partial relationships between optimal effort and each of these parameters were derived by allowing each parameter to vary individually, holding the remaining parameters constant.[4] The results are depicted in figures 4.1, 4.2, and 4.3, respectively.

Marginal Cost (γ)

In figure 4.1, the relationship between optimal effort and γ, the marginal cost of effort, is depicted. The curve is downward sloping, consistent with the general comparative static results in section 4.3.2.

Complexity (C)

In the previous section we saw that an increase in C could in general have two opposing impacts on the optimal level of effort, leaving the sign of the relation undetermined. The relationship between optimal effort and complexity for the parametric specification is illustrated in figure 4.2. The graph is in line with the suggestions from the literature discussed in section 4.2: we find an inverted U-shaped relationship between complexity and effort. Effort initially increases with complexity up until the choice becomes too difficult and effort starts decreasing. Thus figure 4.2 clearly illustrates that the model *can* explain the inverted U-shaped relationship suspected to exist between effort and complexity. Of course, other functional forms or other distributions of ε and Z may give a different pattern. For example, under REIC rather than REDC, a positive relationship results across the entire range.

[4] The chosen benchmark values are $\gamma = 0.152$, D = 1 and C = 1. The basic shapes of the curves do not change with the benchmark values.

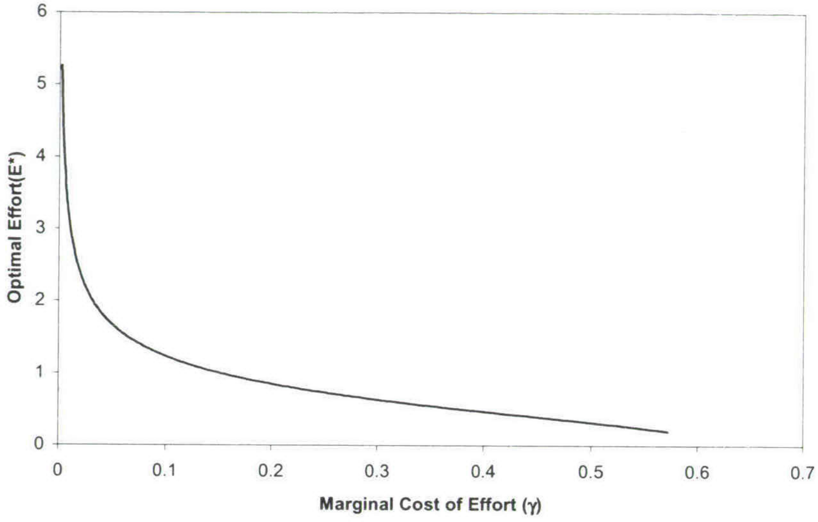

Figure 4.1: Optimal Effort vs. Marginal Cost

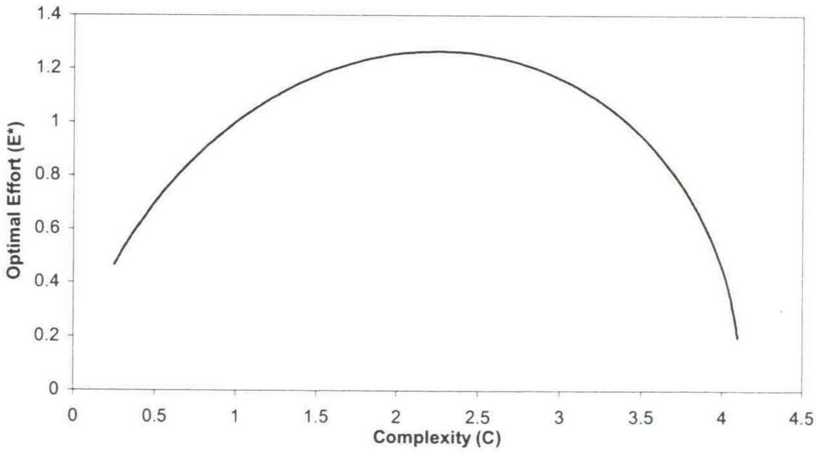

Figure 2: Optimal Effort vs. Complexity

Utility Difference (D)

The relationship between effort and D for our specification is shown in figure 4.3. Effort is decreasing in D for high values of D, consistent with the earlier studies. For low values of D, however, the direct effect (D1) dominates and the optimal effort level increases with D.

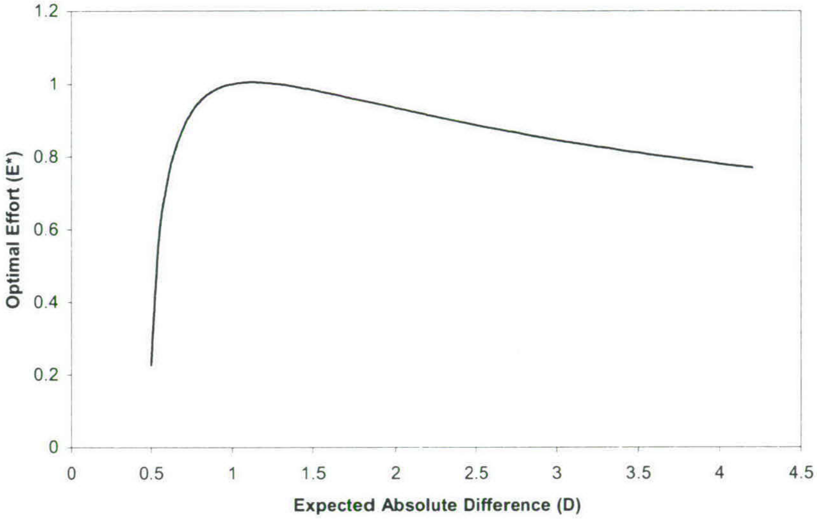

Figure 4.3: Optimal Effort vs. Expected Absolute Differene

4.4 Empirical Analysis

The theoretical model suggests the existence of relationships between the level of effort applied to a given choice task and the parameters γ (the marginal cost of effort), D (expected utility difference) and C (choice complexity). To provide external validity for the theoretical model, these relationships are investigated in an empirical study of hypothetical consumer choices of restaurants. In this section, we first discuss the nature of these data (subsection 4.4.1). Next, we discuss the relationships between γ, D and C, and both the observable consumer involvement measures and choice set characteristics (subsection 4.4.2). We will then regress response time on the involvement measures and choice set characteristics, and will discuss the implications of the regression results for the validity of the model discussed in the previous section (subsection 4.4.3).

4.4.1 Data

A survey was conducted to analyse the relationships between response time, consumer involvement measures, product utility differences and choice complexity. The survey consisted of a conjoint choice experiment involving choices between restaurants described by up to 12 attributes (restaurant type, price, menu, style, number of guests, dessert menu, independent bar, opening times, available methods of payment, distance from available parking, available seating places, and level of service). Table 4.1 presents the attributes and their levels.

The preamble to the survey instructed respondents to imagine that they were on a short weekend break in an unfamiliar small town and were deciding on a restaurant to eat at on a Saturday night. Respondents were faced with choice sets containing 2 potential restaurants described by attributes from the aforementioned list, and were asked to choose their preferred option. Respondents to the survey were members of a representative consumer panel of households in The Netherlands, the CentER*data* Panel. Surveys are administered via modems and the Internet. To avoid selection bias, respondents who don't own a PC receive one from the panel organisation. Of the 1535 respondents who were approached for our study, 1465 usable questionnaires were returned.

To elicit information regarding the respondents' degree of involvement with dining out in restaurants, respondents were asked the questions of Laurent and Kapferer's (1985) CIP measure that we already discussed in section 4.2, tailored to restaurant choice. Because part of the sample for our study also participated in another survey and respondent burden per week is restricted by the panel organisation, involvement questions were administered to only 1052 respondents. Appendix 4.C provides details of the construction of the CIP measures.

Table 4.1: Attributes and levels used in the experiment

Attribute	Base	Level 1	Level 2	Extra Level
Restaurant type	Small Restaurant	Restaurant	Hotel-Restaurant	Hotel-Restaurant
Average entrée price	$ 8	$ 10	$ 15	$ 20
Menu	Basic Menu	Occasionally altered	Extensive	Very extensive
Style	Business	Modern	Old-fashioned	Very old-fashioned
Number of guests	Reasonably busy	Quiet	Reasonably busy	Very busy
Dessert menu	Only Ice-cream	Occasionally altered	Extensive	Very extensive
Separate bar area	Yes	Yes	No	-
Closing time	9 pm	10.30 pm	9 pm	-
Methods of Payment	Cash only	Cash, debit or credit card	Cash only	-
Parking	100 m away	In front of restaurant	300 m away	-
Seating available	Near entrance	Near window and inside		-
Personnel	Only owner working	A lot of personnel	Only a few personnel	-

For the purpose of the conjoint choice experiment, the sample was divided into 5 groups. Within each group, respondents received identical questions. Between groups, choices differed in several ways: the number of questions, the number of attributes and the difference in levels between attributes. These different treatments provide a range in the levels of product utility differences and complexity. A summary of the choice questions asked to each group is provided in table 4.2.

Table 4.2: Description of choice sets per group

	Number of choice sets	*Number of attributes*	*Number of alternatives*	*Number of observations*	*EIP's*
Group 1	9	6	2	314	35
Group 2	9	6	2	323	35
Group 3	5	3	2	221	17
Group 4	9	12	2	207	71
Group 5	9	12	2	206	71

Each attribute was presented at two levels in every group. Orthogonal fractional factorial designs were used to create hypothetical restaurant profiles (Green 1974, Louviere and Woodworth 1983). Orthogonal arrays provide a parsimonious means for constructing product profiles while ensuring that main-effect parameters can be estimated independently. Each choice set contained one restaurant from the experimental design and one "base-alternative" which was constant across all choice sets for each group. In addition to the chosen alternative, response times were recorded for all choice questions separately. Response time is the dependent variable in our regressions. The explanatory variables are based on the (respondent specific) involvement measures, and some choice question specific variables that serve as proxies for utility difference and complexity. As in several other studies, we found no evidence of separate effects of the involvement factors interest and pleasure, and we therefore combine these into one factor. Thus the involvement factors lead to four explanatory variables: *Interest/pleasure*, *Symbolic value*, *Risk importance*, and *Probability of mispurchase*.

To obtain a measure of the variation in utility difference between the products in different choice sets, a multinomial logit model was used to estimate consumer preferences for each attribute (Ben-Akiva and Lerman 1985). These estimates were then used to obtain predictions of the utility of each product in each choice set. The absolute values of the differences in these predicted utilities between the two products in each choice set were then calculated and taken as a choice question specific proxy for variation in D.[5] Since the

[5] This procedure is somewhat *ad hoc* since the multinomial logit model ignores preference heterogeneity across respondents. Still, using the mean preference parameters in a mixed logit model with heterogeneous consumers gives almost identical results.

theoretical model does not predict the sign of the relationship between D and the optimal level of effort, we have no prior expectation of the sign of the effect of this regressor on response time.

As a measure of choice complexity across choice sets we use EIP's: the larger the number of EIP's, the more complex the choice problem. To calculate the number of EIP's, we assume that respondents evaluate all the attributes of all the alternatives and calculate the required number of cognitive steps to determine which product in the choice set has the highest utility. Note that even if respondents do not use a compensatory decision strategy, the number of EIP's computed in this way will serve as a reasonable proxy of choice complexity. It is always increasing in both the number of alternatives and the number of attributes describing each alternative, two well-recognised components of choice complexity, and will be strongly correlated with the number of EIP's required for other decision rules (Johnson and Payne 1985). Since EIP's proxy complexity but the effect of complexity on effort is not determined, the theoretical model does not lead to an expected sign of the effect of EIP's on response time.

Finally, we also include a dummy for the first question (1 for the first question, 0 for other questions). The reason is obvious: the first question will take more time since the consumer has to become familiar with the nature of the questions. Including additional dummies for questions other than the first did not change any of the results.

4.4.2 Relationships between Involvement Components and Model Parameters

Interest/Pleasure component

Individuals who find a product more interesting or receive more pleasure from a product may find the choice task more relevant and enjoyable. We therefore expect that they have lower opportunity costs of the processing time spent on the choice task. In terms of our model, this implies that they have a lower marginal cost (γ) for each additional unit of effort. Since the effect of γ on E is negative (see section 4.3), this implies that we expect that response time will increase with interest/pleasure.

Symbolic value component

We expect the symbolic or sign value of the product to be positively associated with the pay-off to a correct choice, without directly affecting the probability of correct choice. As explained at the end of subsection 4.3.2, this means in our framework that symbolic value is inversely related to γ, the relative cost of effort. As in the previous case, this implies that we expect response time to increase with symbolic value.

Risk Importance component

The risk importance component measures how the consumer weighs the negative consequences of making the wrong choice. Higher risk importance means attaching more weight to the utility gain compared to the cost of effort. Risk importance has no direct effect on the probability of mispurchase. Thus, as in the previous case, in our framework, a higher score on risk importance means a lower γ. Thus we expect that response time will rise with risk importance.

Probability of Mispurchase component

The consumer's evaluation of the probability of mispurchase can be regarded as a measure of the level of uncertainty the individual feels with respect to purchases in the particular product class, and can be seen as a subjective measure of the respondent's perception of choice complexity. We thus expect that the probability of mispurchase is positively related to C. The results in subsection 4.3.2 then imply that the sign of the relationship between response time and probability of mispurchase is not determined by the theoretical model. According to subsection 4.3.3, the relationship could be hump-shaped (figure 4.2). We can say, however, that this regressor is expected to have the same sign as the EIP's, since both are positively related to complexity. If the relation between E and C is positive, both regressors should have a positive coefficient, etc.

4.4.3 Results

Two OLS regressions were conducted to analyse the relationships between consumer response time as a proxy of choice effort, and our explanatory variables. The first estimation regressed the individual CIP consumer involvement measures against response time while the second regressed estimated product utility differences and EIP's across choice sets against response time.[6]

Table 4.3: Response time vs. involvement components*

Variable	*Estimate*	*t-value*
Constant	11.427	10.058
Interest/Pleasure	0.121	2.424
Symbolic	0.043	0.582
Risk Importance	0.267	2.369
Prob. of Mispurchase	0.198	4.005

* N = 1052 observations, R^2 = .020

Table 4.3 describes the relationships between these involvement components and response time. Three of the four components are significant, only the Symbolic value component is not significant. The signs for *Interest and pleasure, Risk importance*, and *Symbolic value* are as expected (see subsection 4.4.2). The positive sign of *Probability of mispurchase* implies that effort increases with complexity. Because figures 4.2 and 4.3 suggest non-linear patterns, we also tested if including squares of the involvement variables would improve the fit of the regressions. None of the square terms were found to be significant.

The second equation explains response time from choice question specific variables. The results are presented in table 4.4. The estimates show that across choice tasks, consumer

[6] The units of observation are all respondent/question combinations. Qualitatively similar results are obtained if, in the first regression, response times are averaged over all questions and each respondent is one unit of

choice effort falls significantly with product utility difference and increases with higher task complexity. The latter is in line with the positive effect of complexity on effort, which we already derived from table 4.3. Some non-linear effects were also evaluated in further regressions (quadratic, cubic, log's) but did not indicate that the sign of these effects changed as product utility or complexity increased.

Table 4.4: Response time vs. expected utility difference D and EIP's*

Variable	*Estimate*	*t-value*
Constant	4.450	9.36
Question 1 dummy	21.784	45.61
D (expected product utility difference)	-3.390	-9.97
EIP's (choice task complexity)	0.365	42.01

* N =1271 observations, $R^2 = 0.263$

Summarising, the empirical results support the theoretical model. Where the theoretical model predicts an unambiguous sign, this sign is always found. In all cases but one (*symbolic value)*, it is also significant. Moreover, the signs of EIP's and *Probability of mispurchase* are the same, and this is also what the theoretical model predicts.

4.5 Discussion and Conclusion

The purpose of this chapter was to develop and test a model that relates the effort applied in a particular choice situation to choice set complexity, the utility difference between the products or the degree of conflict, and personal characteristics captured here by the level of consumer involvement. A theoretical model was introduced, and its implied relationships were derived for the general case as well as a specific functional form. The model is not only

observation, or in the second regression, response times are averaged over consumers and each question is one unit of observation. The same regressors remain significant, though t-values become smaller.

consistent with many observations in the existing literature on consumer choice, but also provides insight into the underlying trade-offs that influence the decision process. In particular, the derived relationships between the level of effort applied in a choice situation and choice environment variables such as choice complexity and conflict are in line with prior research.

The influence of personal characteristics is analysed using consumer involvement. After discussing how various components of involvement may influence the parameters of the model, hypotheses were formed regarding the expected overall influence on consumer effort. An empirical application to restaurant choice in The Netherlands showed strong support for the model: basically all hypotheses were confirmed and none were conclusively rejected.

Although these results are encouraging and suggest that the model is able to capture important aspects of consumer decision strategies, there are also some clear limitations. The model has only been developed for the simple case of a choice between two products. A valuable extension would be to augment the range of choice situations for which the model is applicable by allowing consideration of choices between multiple products. In addition, the relationship between response time and various social demographics could provide insightful results. For example, the level of education may have an impact on the marginal cost of effort. The degree to which the results found here can be generalised to different product categories is also unknown. Finally, it would be interesting to examine to what extent the functional form assumptions influence the model's behaviour and to test competing functional forms against real-world data.

Appendices

4.A Proof that (NIRE) and (USYM) imply (SOC)

As seen in section 4.3 of the chapter, the consumer faces the following maximisation problem

$$(4.12)\qquad \mathrm{Max}_{E>0}\qquad E\{P(\varepsilon > -D\,|\,Z\,|\,a(E;C)|\,Z)\times D\,|\,Z\,|\}-\gamma E$$

with first order condition

$$(4.15)\qquad \gamma = E\{f_\varepsilon(-D\,|\,Z\,|\,a(E;C))\times(D\,|\,Z\,|)^2\}\times\frac{\partial a}{\partial E}$$

$$(4.23)\qquad = \int_{-\infty}^{\infty} f_\varepsilon(-D\,|\,Z\,|\,a(E;C))\times(D\,|\,Z\,|)^2 f_Z(Z)dZ\times\frac{\partial a}{\partial E}$$

or, equivalently

$$(4.24)\qquad \gamma = 2\int_0^{\infty} f_\varepsilon(-DZa(E;C))\times(DZ)^2 f_Z(Z)dZ\times\frac{\partial a}{\partial E}$$

The second order condition requires

$$(4.25)\qquad \frac{d}{dE}\left[2\int_0^{\infty} f_\varepsilon(-DZa(E;C))\times(DZ)^2 f_Z(Z)dZ\times\frac{\partial a}{\partial E}\right]\le 0$$

and differentiating the expression in brackets yields:

$$(4.26)\qquad 2\int_0^{\infty}\left[\underbrace{f'_\varepsilon(-DZa(E;C))\times\left(\frac{\partial a}{\partial E}\right)^2 DZ}_{\substack{\le 0\text{ for all }Z\\ \text{(USYM)}}}+\underbrace{f_\varepsilon(-DZa(E;C))\times\frac{\partial^2 a}{\partial E^2}}_{\substack{\le 0\text{ for all }Z\\ \text{(NIRE)}}}\right]\underbrace{(DZ)^2 f_Z(Z)}_{\ge 0\text{ all }Z}dZ\le 0$$

and it can be seen from (4.26) that the (USYM) and (NIRE) conditions are sufficient to ensure the second order condition holds.

4.B Proof of (4.21) and (4.22)

Consider the consumer maximisation problem given in equation (4.12) in section 4.3:

$$(4.12) \qquad \mathrm{Max}_{E>0} \qquad E\{P(\varepsilon > -D\,|\,Z\,|\,a(E;C)|\,Z) \times D\,|\,Z\,|\} - \gamma E.$$

Taking expectations over the ranges of both ε and Z this becomes

$$(4.27) \qquad \mathrm{Max}_{E>0} \qquad \iint 1[\varepsilon > -D|\,Z\,|\,a(E;C)]D|\,Z\,|f(\varepsilon, Z)d\varepsilon\, dZ - \gamma E,$$

where f(ε,Z) is the joint density function for ε and Z. The distribution of Z is symmetric, so this may be rewritten as

$$(4.28) \qquad \mathrm{Max}_{E>0} \qquad 2\iint 1[\varepsilon + DZa(E;C) > 0, Z > 0]DZf(\varepsilon, Z)d\varepsilon\, dZ - \gamma E.$$

The distributional assumptions for the variables ε and Z imposed in section 4.3 are:

$\varepsilon \sim N(0,1)$, and,

$$(4.16) \qquad Z \sim N(0, \pi/2).$$

Thus f(ε,Z) is a bivariate normal density with means (0,0), variances (1, π/2) and correlation zero. Noting that

$$(4.29) \qquad E\{\varepsilon + DZa(E;C)\} = E\{\varepsilon\} + E\{DZa(E;C)\} = 0 + Da(E;C) \times E\{Z\} = 0,$$

since E{ε}= E{Z}= 0 from (4.10) and (4.3), and further, with ε and Z are independent, we have

$$(4.30) \qquad \mathrm{Var}\{\varepsilon + DZa(E;C)\} = E\{\varepsilon^2\} + (Da(E;C))^2E\{Z^2\} = 1 + (Da(E;C))^2\pi/2.$$

Substituting the standardised normal variables

$$(4.31) \qquad z_1 = \frac{(\varepsilon + DZa(E;C))}{\sqrt{1 + (Da(E;C))^2\,\pi/2}}, \text{ and } \qquad z_2 = \frac{Z}{\sqrt{\pi/2}},$$

into (4.28), and further, after noting that with both denominators in (4.31) positive $1[z_1 > 0, z_2 > 0]$ implies $1[\varepsilon + DZa(E;C) > 0, Z > 0]$, the optimisation problem becomes

$$(4.21) \qquad \mathrm{Max}_{E>0} \qquad \sqrt{2\pi}D\iint 1[z_1 > 0, z_2 > 0]z_2 f(z_1, z_2)dz_1 dz_2 - \gamma E,$$

where $f(z_1,z_2)$, the joint density of the transformed variables z_1 and z_2, is a standardised bivariate normal with means (0,0), variances (1,1) and correlation coefficient:

(4.22)
$$\rho=\frac{\operatorname{Cov}(z_1,z_2)}{\sqrt{\operatorname{Var}(z_1)\operatorname{Var}(z_2)}}=E\{z_1\,z_2\}=E\left\{\frac{\varepsilon+DZ\,a(E;C)}{\sqrt{1+(D\,a(E;C))^2\,\pi/2}}\times\frac{Z}{\sqrt{\pi/2}}\right\}$$

$$=\frac{E\left(\varepsilon Z+DZ^2a(E;C)\right)}{\sqrt{\pi/2\left(1+(D\,a(E;C))^2\,\pi/2\right)}}=\frac{E(\varepsilon Z)+D\,a(E;C)\times E\left(Z^2\right)}{\sqrt{\pi/2\left(1+(D\,a(E;C))^2\,\pi/2\right)}}$$

$$=\frac{0+D\,a(E;C)\times\pi/2}{\sqrt{\pi/2\left(1+(D\,a(E;C))^2\,\pi/2\right)}}=\frac{D\,a(E;C)\sqrt{\pi/2}}{\sqrt{1+(D\,a(E;C))^2\,\pi/2}}$$

as seen in the text.

4.C Results of Principal Component Analysis

Involvement Construct

Respondents to the survey were asked 16 questions on their involvement with the product category ‘restaurants’. Each question related to one of the five facets of involvement identified by Laurent and Kapferer (1985) and was drawn from the CIP measure developed by these authors. A principal component analysis was conducted reducing the measured responses into orthogonal components. The results are presented in, table 4.5. It can be seen that only four underlying components are found. It is not uncommon for the principal component analysis to identify fewer than all five separate facets of the CIP measure, due to the high level of correlation between the facets. Laurent and Kapferer also found that only four components were required as two facets loaded onto a single component. The table indicates the loading of each question from each facet on each component. The most relevant loadings for the involvement constructs are shaded to provide a visual representation of the makeup of each component. Ideally, were the data to demonstrate “trait” validity, each facet should load onto only one component. Apart from the *Symbolic value* facet which has a significant loading on both components 1 and 3, the components generally exhibit trait validity. The discriminant validity of each component represents the degree to which each component can be considered as measuring different concepts. With all facets being related to the same concept of involvement it is likely that a significant amount of correlation exists between the facets reducing discriminant validity. Thus several facets may be found to load onto the one component. This is the case for the facets Interest and Pleasure and to a lesser extent the Symbolic value facet. The loading patterns indicate that all of these facets are significant determinants of component 1.

Table 4.5: Principal component analysis

		Component			
Question	*Facet*	1	2	3	4
1	Interest	.613	.085	.046	.089
2	Interest	.720	.166	.162	.030
3	Interest	.603	.281	.212	.038
4	Pleasure	.735	.264	.410	.115
5	Pleasure	.587	.026	.233	.030
6	Pleasure	.736	.268	.386	.052
7	Symbolic	.561	.257	.573	.139
8	Symbolic	.526	.311	.609	.103
9	Symbolic	.568	.249	.540	.013
10	Risk Importance	.053	.117	.113	.797
11	Risk Importance	.111	.347	.114	.410
12	Risk Importance	.187	.505	.060	.450
13	Prob of Mispurchase	.054	.679	.278	.111
14	Prob of Mispurchase	.017	.576	.299	.280
15	Prob of Mispurchase	.072	.746	.223	.026
16	Prob of Mispurchase	.079	.720	.303	.255

Although each facet loads on each component to some degree, considering only the more significant and/or discriminating loadings, we conclude for this study that the four components relate mostly to the following four distinct facets:

Component 1: *Interest and Pleasure*

Component 2: *Probability of mispurchase*

Component 3: *Symbolic value*

Component 4: *Risk importance*

The first component is labelled as relating to only *Interest and Pleasure*, even though the *Symbolic value* facet also played a significant role in its calculation because the symbolic facet shows a high discriminant validity with component 3. Even though it lacks some trait validity through its strong association with component 1, component 1 is likely to pick up the part of the *Symbolic value* facet which is correlated to *Interest and Pleasure*. Due to the orthogonality of the components, only those dimensions of the *Symbolic value* facet which are independent *of Interest and Pleasure* are being picked up by component 3.

Chapter 5

Effort, Decision Strategy and Choice: How many attributes do consumers consider?

In choice situations with few products and many attributes the standard fully compensatory assumption that all attributes are used to compare the alternatives is unrealistic. We use stated preference data with additional information on the importance ratings of attributes, and which attributes were always or never used in the choice decisions. The raw data suggest that less than half of the attributes are always used, while more than one third are never used. We develop a two-stage model in which consumers first decide which attributes to incorporate in their decision process, and then use a compensatory choice strategy using only these attributes. The main feature of the model is the link between the preference weight given to an attribute and the probability it is used in the actual choice process. We then formulate an empirical model that jointly explains choices, answers to importance ratings questions, and answers to questions on whether attributes were always or never used. The model is estimated with simulated maximum likelihood. We find, for example, that price is only considered in about 59% of all choice problems. We also find that the probability that an attribute is considered increases with the respondent's response time, confirming that more involved consumers who spend more time on their choices, are using strategies that come closer to fully compensatory decision making.

5.1 Introduction

The study of the decision processes used by consumers when faced with a choice task is important for understanding consumer behaviour. Models of consumer choice have achieved popularity across a range of disciplines, due to their ability to provide valuable insight into the market behaviour of consumers. In particular, marketing researchers have used models of consumer choice for market segmentation, product positioning and predictions of consumer choice. Our objective in this chapter is to gain an understanding of which attributes as well as how many attributes consumers consider in a multi-attribute decision task and to see how these outcomes relate to consumer preferences.

To this end we develop a model for choosing between two or more products that generalises the mixed multinomial logit model (McFadden and Train 2000) and incorporates the possibility that respondents base their choice on a limited number of product attributes only. The starting point is the random utility framework, where the utility of a product is the sum of contributions from all attributes. The weights of the attributes vary across respondents and are thus treated as random coefficients. The well-known mixed multinomial logit model uses this framework. It assumes that products are compared on the basis of all attributes in a fully compensatory fashion.

The existing literature provides evidence that respondents do not always make their decisions in a fully compensatory manner, but instead often use simplifying strategies not requiring comparisons of all products on all attributes. In this chapter, we look at the choices between a few products with many attributes. Here not considering certain alternatives at all is not an issue, but not taking into account all of the attributes is. We generalise the mixed logit model by including threshold values. If the difference between the utility contributions of a certain attribute across the products in the choice situation is below the threshold, the attribute is not taken into account in the choice decision. Thus our model is characterised by a direct link between the strength of preference an individual has for an attribute, and whether an attribute is considered or not. We allow for heterogeneity across respondents in preferences (through random preference coefficients) as well as choice strategies (through random thresholds). Moreover, the thresholds in our model vary with the nature of the choice sets (i.e., choice complexity) as well as the amount of effort the respondent has put in (i.e., response time). The framework we provide encompasses a range of strategies including the fully compensatory decision rule as a special case.

In order to estimate this model, we use a data set that contains additional information that is usually not provided in data on consumer choice. We have a large survey of respondents who not only provide stated preference (SP) choice data, but also provide importance ratings on all the attributes, and supplementary information on which attributes they used in all their choices, and which attributes they never used. Particularly the latter data allow us to directly infer how often attributes were used. With the help of the additional information we are able to disentangle the various strategies individuals use, so that both consumers' preferences and strategies can be jointly modelled. With choice data only, the broad range of decision rules encompassed by a model such as the one we present would lead to a non- or very weakly identified model. Finally, response times for the choice questions are recorded in this data set as well, and these will be used as a proxy for cognitive effort. We will include response time as an explanatory variable for the thresholds, which determine whether attributes are used or not. The model is estimated using a simulated maximum likelihood technique. Our empirical findings confirm that people who spend less effort follow decision strategies that involve fewer attributes.

The chapter is structured as follows. In the next section, we position our study in the existing literature on compensatory and non-compensatory decision strategies. In section 5.3, we present formally the model, characterised by a two-stage decision strategy. We discuss an econometric model for implementing this decision strategy, and we discuss how this model can be estimated, using both the SP choice data and the extra information on individual response times and use of attributes. In section 5.4, we focus on the empirical application. We first describe the data and the main relationships between the variables in the model. We then discuss the estimates and do some additional calculations, employing new techniques developed by Revelt and Train (1999), to illustrate how the model works and its implied relation between preferences and the attributes people consider. Section 5.5 concludes.

5.2 Models of Consumer Choice

Many choice modelling applications in the marketing literature assume individuals use a fully compensatory utility maximising decision process. This assumes that in determining the value of any particular product, consumers consider the levels of all attributes for that product simultaneously, weighing up the relative importance of each attribute to obtain the overall utility of the product. This process is termed fully compensatory (or simultaneous) because a product that is deemed deficient on one particular attribute can still be selected if this deficiency is compensated by high scores on other attributes. The consumer repeats this process for each product in the choice and then chooses the product providing maximal utility. The well-known (multinomial) Logit, and Probit models are based upon this decision strategy (see Ben-Akiva and Lerman 1985).

Increasing evidence in the literature on consumer choice suggests that consumers frequently do not follow a fully compensatory choice process, but rather prefer to employ simpler decision rules (Wright 1975, Gensch and Javalgi 1987, Chaiken 1980, Johnson et al. 1989, Fader and McAlister 1990, Russo and Dosher 1983, Payne et al. 1993). The model introduced in the current chapter allows for simplification of the decision task by permitting individuals to consider only a subset of product attributes rather than the complete set of information available. Few researchers would refute the concept that alternatives to the fully compensatory choice process are often much closer to the actual choice process decision-makers use to make choices. Individuals may employ a variety of simpler choice strategies, which ignore potentially relevant problem information, to reduce the level of cognitive effort or mental processing required for making choice decisions (Abelson and Levi 1985, Payne et al. 1988). Examples of well-documented alternative strategies requiring less effort on behalf of the decision-maker are the satisficing model (Simon 1955), elimination by aspects (Tversky 1972), and the lexicographic or conjunctive procedure (Dawes 1964). The main justification for the use of simplifying strategies is the desire of consumers to reduce the required level of mental effort involved in the decision process (Shugan 1980, Swait 2000, Swait and Adamowicz 2001). When selecting a decision strategy, consumers trade-off the costs of this required mental effort with the benefits, primarily the ability of a decision process to select the best alternative (Russo and Dosher 1983, Johnson and Payne 1985, Payne et al. 1988, Bettman et al. 1988, Bettman et al. 1990).

Several previous attempts to model simplifying strategies mostly focus on hierarchical attribute processing models. These assume that product attribute information is processed in a contingent way as in the lexicographic and elimination by aspects choice processes. In these models the decision-maker is assumed to have a pre-specified order of importance across the various attributes and considers each in turn according to this order. In these types of models, for the particular attribute being considered, products are eliminated if they either do not possess the highest level for an attribute or fail to meet a set criteria or cut-off. After all but one product has been eliminated, the remaining product is chosen. Examples include the HIARC model (Gensch and Svestka 1979), its probabilistic version, the maximum likelihood hierarchical (MLH) model (Gensch and Svestka 1984), Tversky and Sattah's (1979) PRETREE and its' extensions (Gensch and Ghose 1992, Gensch and Ghose 1997), the 'elimination by cut-offs' model of Manrai and Sinha (1989). Currim, Meyer and Le (1988) infer hierarchical models without requiring prior specification of a particular decision strategy. Other papers assuming the hierarchical framework with ordered attribute selection and attribute cut-offs are Grether and Wilde (1984), Klein and Bither (1987), Huber and Klein (1991), and Sethuraman et al. (1994). These latter studies have concentrated on examining how and why attribute cut-offs are formed.

It is well accepted in the literature on consumer choice that consumers may reduce the extensiveness of their decision process by not necessarily considering all attributes (Gensch and Javalgi 1987, Park and Parker Lessig 1981, Swait and Adamowicz 2001, Moore and Lehmann 1980, Shugan 1980). In the model we introduce in this chapter, consumers make choices based on a subset of the attributes. The attributes they consider are then evaluated in a compensatory manner. The model may be seen as consisting of two stages: in the first stage consumers screen the number of *attributes* to be considered down to a smaller number, and in the second stage the remaining attributes are considered simultaneously, allowing for compensatory tradeoffs among the attributes. This is somewhat reminiscent of the work of Gensch (1987) who proposes a two-stage model of choice where consumers initially use a non-compensatory process to screen down the number of *alternatives* to a manageable number via attribute processing and then consider the remaining attributes in a compensatory fashion. In both models consumers use a simplifying process to reduce the magnitude of the choice problem and, following this, a more rigorous (and mentally demanding) compensatory process is carried out. For a similar reason our model can be compared to models of consumer consideration sets which model how the number of alternatives in the choice set is reduced by consumers (Swait and Ben-Akiva 1987a,b, Roberts and Lattin 1991, Andrews and Srinivasan 1995, Ben-Akiva and Boccara 1995, Allenby and Ginter 1995, Chiang et al. 1999). These have concentrated on consideration sets with respect to *alternatives*. A parallel may be drawn with our model of choice based on a considered set of *attributes*. In choice situations where many products with few attributes have to be considered, simplifying strategies will be used to reduce the set of alternatives to a manageable size. On the other hand, we focus on choice situations where only few alternatives are considered, but all these products have many attributes. In such a situation, a fully compensatory strategy requires adding up the utility differences due to all the separate attributes. It seems quite natural that respondents then compare the alternatives using what they consider the most relevant attributes only. It is this idea that we incorporate in a formal model and then investigate empirically.

5.3 Theory and Econometric Model

This section presents the theoretical and econometric model, used to analyse consumers' SP choice data while simultaneously incorporating individuals' reported information on the use and importance of the respective attributes as well as consumer response times. As discussed in the previous section we do not assume that the consumers' decision is necessarily based on the full range of attributes presented for each product as in a standard fully compensatory model. Rather only those attributes that are deemed to have a large enough impact on utility (above a certain threshold level) are considered. We first describe the formation of this consideration set. Next, the decision process given the consideration set is modelled. In the third subsection, we explain how the empirical model incorporates the additional attribute-specific information provided by the respondents, based upon questions on whether the respondent used the respective attributes always or never, and on importance ratings of the attributes. This subsection also presents distributional assumptions and discusses scaling and identification issues. Finally, an explanation of the procedure used to estimate the model is given in subection 5.3.4.

Throughout, we will use the following notation:

i	respondent ($i=1,\ldots,N$)
k	attribute ($k=1,\ldots, K$); K is the total number of attributes
s	choice situation ($s=1,\ldots,S$); S is the total number of choice situations

j alternative ($j=1,\ldots,J(s)$); $J(s)$ is the number of alternatives in choice situation s

$X_j = (x_{j1},\ldots,x_{jK})'$ vector of attributes of alternative j; X_j does not include a constant.

We will follow the standard assumptions on preferences, and assume that the utility of each product is given by the sum of utility contributions of all the attributes. Thus we do not allow for interactions between the various attributes. Let the utility derived from the k-th attribute of alternative j for respondent i be given by:

$$U_{ijk} = x_{jk}\beta_{ik} \tag{5.1}$$

where x_{jk} is the value of the k-th attribute of alternative j, and β_{ik} is the individual-specific slope coefficient for this attribute.

5.3.1 The Decision Rule, Stage 1: The Set of Considered Attributes

The motivation behind this chapter is the proposal that individuals, when faced with a choice between few products, characterised by a reasonably large number of attributes, may not necessarily evaluate each product on all attributes, but instead may select only a few of the more salient attributes for consideration. Thus the respondent is assumed to form a consideration set of attributes and to make a choice based exclusively on the attributes in that set. Whether an attribute k is used in a given choice situation s depends on the contribution (in absolute value) of that attribute to the utility difference between the alternatives in the set. For a choice s between two alternatives (j and j'), this difference is given by[1]

$$\Delta U_{ik}(s) = |x_{j'k} - x_{jk}||\beta_{ik}| \tag{5.2}$$

For a choice situation with more than two alternatives, we will assume that the same attributes are used in comparing all pairs of alternatives. It therefore seems reasonable to assume that the utility difference relevant for whether or not an attribute is considered, is the maximum of all pair-wise differences:

$$\Delta U_{ik}(s) = \max\{\, |x_{j'k} - x_{jk}||\beta_{ik}|;\ j,j' \in \{1,\ldots,J(s)\}\,\} \tag{5.3}$$

[1] For some of the attributes in our data, the possible values are unordered, and a somewhat different expression for $\Delta U_{jk}(s)$ applies (using dummy variables for the possible outcomes). This extension is straightforward, though it complicates notation.

The criterion for inclusion in the consideration set is that $\Delta U_{ik}(s)$ exceed some threshold value. We denote the threshold value for individual i in choice situation s by T_{is}. The decision on whether an attribute is in the consideration set for choice situation s is determined by

(5.4) Attribute k is used if and only if $\Delta U_{ik}(s) > T_{is}$

Applying this criterion to all attributes gives the consideration set for individual i in choice set s, denoted by C(i,s):

(5.5) $C(i,s) = \{k \in \{1,\dots,K\};\ \Delta U_{ik}(s) - T_{is} > 0\}$

From (5.4) it is clear that the higher the value for $\Delta U_{ik}(s)$ is, the more likely the k-th attribute will be considered. Thus when either the difference in the levels of attribute k between products increases, or the individual's (absolute) preference weight for the attribute increases, the probability that the attribute is considered will rise. This creates a link between consideration set and preferences: the more important attributes have the largest chance to be included in the consideration set.

The $\Delta U_{ik}(s)$ terms will not only vary across individuals (through preferences) but also with choice contexts (through the attribute levels x_{jk}). Thus the set of considered may vary across both individuals and choice tasks.

Additional variation in the set of considered attributes is introduced through variation in thresholds. We assume that the threshold is constant across all attributes but may vary across both respondents and choice situations. The reason that the threshold varies across respondents is that respondents are heterogeneous with respect to their choice of decision strategy. For example, a very involved consumer will typically put a lot of effort in each choice and thus will have a lower threshold, bringing him closer to a fully compensatory decision strategy.

Furthermore, consumers will probably compensate for additional complexity by putting in more effort. Thus if choice problems become more complex, we would expect lower thresholds and less simplification. This explains why we also allow the thresholds to depend on the complexity of the choice situation.

To model such threshold heterogeneity we use the following specification:

$$T_{is} = Z_{is}\gamma + \varepsilon_{is} \tag{5.6}$$

where Z_{is} is a vector of explanatory variables, including a constant term, and ε_{is} reflects unobserved heterogeneity in thresholds.

As mentioned in the previous section, one special feature of the data set we use to implement the model is the availability of response latencies measuring the time taken for respondents to answer each choice question. The worth of recording response times has previously been recognised as providing valuable information about the extensiveness of a consumers' decision process. The reader is referred to Haaijer, Kamakura, and Wedel (2000) for a comprehensive summary of the use in both psychology and marketing. We expect that individuals who spend more time on their choices, consider a larger number of attributes. Accordingly we include individual response times in Z_{is}, expecting higher response times to be associated with lower threshold levels T_{is}. Moreover, as discussed above, we expect choice set complexity to play a role. Our sample consists of six groups of respondents who were given choice problems of different complexity (see section 5.4). To account for these shifts in complexity between groups, we include dummy variables for these groups in Z_{is}.

5.3.2 The Decision Rule, Stage 2: Compensatory Evaluation of Considered Attributes

In the second stage of the decision process, we assume the decision-maker analyses the set of considered attributes determined in stage 1 in a simultaneous compensatory manner to form approximate values of the overall utility associated with each alternative. The framework we use is the same as in a fully compensatory choice rule however, the utility values now only contain the contributions of the attributes that are included in the consideration set of the given choice situation. For choice situation s the utility of alternative j to respondent i is given by:

$$V_{ij}(s) = \sum_{k \in C(i,s)} x_{jk}\beta_{ik} \qquad (j=1,\ldots,J(s)) \tag{5.7}$$

Accounting for errors in the same way as in models using the random utility framework (such as the multinomial logit), we assume that respondents base their choice on an unobservable latent variable, $V_{ij}(s)^*$, composed of the structural utility in (5.7) and a random component:

(5.8) $V_{ij}(s)^* = V_{ij}(s) + e_{ijs}$

The decision rule is then

(5.9) Choose c if $V_{ic}(s)^* \geq V_{ij}(s)^*$ for all $j = 1,\ldots,J(s)$

Thus the product is chosen which is judged to provide the highest utility, after compensatory evaluation of the attributes in the consideration set.

5.3.3 Econometric Model

To implement the choice model presented in the previous section on a SP data set, we first need some distributional assumptions. We also need to specify how the additional attribute importance ratings and information on which attributes are always or never used, are incorporated in the model.

Distributional Assumptions

To allow for heterogeneity in preferences across individuals, the vector of attribute slope coefficients $\beta_i = (\beta_{i1},\ldots,\beta_{ik},\ldots,\beta_{iK})'$ in (5.1) are treated as a vector of random coefficients, using the following specification:

(5.10) $\beta_{ik} = b_k + u_{ik}, \quad k=1,\ldots, K,$

(5.11) $u_i = (u_{i1},\ldots,u_{iK}) \sim N(0,\Omega).$

It is assumed that the same β_i is used by respondent i in all choice situations. Unobserved characteristics of respondent i enter through the u_{ik}. We assume that the u_{ik} are drawn from a K-variate normal distribution with mean zero. The parameters in the K×K matrix Ω need to be estimated. For computational convenience, we assume that Ω is diagonal, so that only K standard deviations (ω_k) need to be estimated.[2] Since the random coefficients β_{ik} (or the u_{ik}) do not vary with choice situations or alternatives, and since they are independent across individuals, the correlation structure of choices across individuals, choice situations, and alternatives, identifies the variances of the random coefficients.

Similarly, the unobserved heterogeneity in the thresholds term in (5.6), ε_{is}, is assumed to be normally distributed:

(5.12) $\varepsilon_{is} \sim N(0,\sigma_\varepsilon^2)$,

ε_{is} is independent of other random variables in the model (such as β_i).

Furthermore, we assume that the random components, e_{ijs}, in (5.8) follow independent GEV(I) distributions. This gives the familiar multinomial logit form for the choice probabilities, conditional on the parameters β_i and the threshold T_{is}:

$$(5.13) \qquad P_{is}(c|\beta_i,T_{is}) = P(\text{i chooses alternative c in situation } s|\beta_i,T_{is}) = \frac{\exp(V_{ic}(s))}{\sum_{j=1}^{J(s)}\exp(V_{ij}(s))}.$$

Thus the only difference with the standard mixed logit framework is the fact that only the attributes in the consideration set are used to construct the product utilities, rather than all the attributes.

Additional Information

After having answered all the choice questions, respondents were asked to indicate the attributes they had always used and the attributes they had never used. Following this they were asked to rate each attribute's importance on a scale of 1 to 7. We incorporate these additional data in a manner consistent with our construction of attribute consideration sets.

Attribute Consideration - Always/Never Used

The framework already developed for determining the consideration set suggests an obvious approach for incorporating the information on whether attributes were always or never used. The answer to the question: "did you always use this attribute?" is driven by the minimum value of $\Delta U_{ik}(s)$ over all choice problems s=1,…,S faced by the respondent. If the minimum value lies above the individual's threshold value, the attribute should always be present in the individual's consideration set. We allow for reporting error as follows:

---

[2] The assumption that random coefficients are normally distributed could easily replaced by another assumption. For example, a discrete distribution where each mass point represents a market segment, is an interesting

(5.14) The respondent reports that he has always used the attribute if

$$\text{Min}\{\Delta U_{ik}(s)|s=1,\ldots,S\} - T_{is} + v_{ik} > 0$$

Here $v_{ik} \sim N(0,\sigma_v^2)$ represents the possibility that someone gives the wrong answer. It is assumed that the v_{ik} are mutually independent and independent of the u_{ik}, ε_{is}, and the e_{ijs}.

Similarly, the answer to the question "did you never use this attribute?" is driven by the maximum of $\Delta U_{ik}(s)$ over all choice problems s=1,…,S the respondent faces:

(5.15) The respondent reports that he has never used the attribute if

$$\text{Max}\{\Delta U_{ik}(s) - T_{is}|s=1,\ldots,S\} + w_{ik} < 0$$

with $w_{ik} \sim N(0,\sigma_w^2)$ representing another reporting error. The w_{ik} are assumed to be mutually independent as well as independent of the u_{ik}, ε_{is}, e_{ijs}, and the v_{ik}.

Attribute Importance Ratings

The attribute importance ratings refer to scores provided on a scale of 1 (indicating the attribute was not important) to 7 (very important). Thus the observed ratings are an ordered categorical variable with R=7 possible outcomes, which we label r = 1,…,R. The ratings data indicate the overall importance of each attribute, as viewed by the respondent after evaluating all the choice sets. Therefore it seems plausible that the ratings should be driven by the average of the utility difference in (5.3) over all choice sets s=1,…,S. Allowing for some noise in the answers to the importance ratings, we thus specify the following ordered probit equation:

(5.16) $$R_{ik}^* = 1/S\sum_{s=1}^{S}\Delta U_{ik}(s) + \phi_{ik}$$

$$R_{ik} = r \text{ if } m_{r-1} < R_{ik}^* \leq m_r$$

$$\phi_{ik} \sim N(0,\sigma_\phi^2)$$

Thus respondent i reports a rating of $R_{ik} = r$ for attribute k if the latent variable R_{ik}^* lies within the categorical boundaries m_{r-1} and m_r. R_{ik}^* is interpreted as the (unobservable) true importance of attribute k for consumer i. The bounds $(-\infty = m_0 <)\ m_1 < \ldots < m_{R-1}\ (< m_R = \infty)$

alternative. There seems to be no common view in the literature which assumptions give the best fit to the data.

are unobserved parameters which can be estimated. It is assumed that the random error terms, ϕ_{ik}, are mutually independent and independent of u_{ik}, ε_{is}, e_{ijs}, v_{ik} and w_{ik}.

Normalisation and Identification

As for the standard multinomial logit model the scale of the utility function is normalised via a specific choice of the scale of the errors e_{ijs}. Therefore the scale parameter of the GEV(I) variables is set to unity. The location of the utility function is identified by excluding a constant term from X_j, and as a consequence the distributions of the random coefficients βi are identified. With β_i fixed, the vector of parameters, γ, from the threshold equation (5.6), and the scale of the respondent specific terms ε_{is}, are also identified. In addition the scale of the error terms v_{ik} and w_{ik} in (5.14) and (5.15) respectively are now identified. The only remaining parameters to be discussed are the category boundaries $m_1,\ldots,m_{R-1}$ arising in the specification of the ordered probit model in (5.16) for the attribute ratings data. Normally, in a model for the ratings only, some normalisation of scale and location would be necessary. However, from the normalisation already imposed on the choice part of the model the scales of the random coefficients are identified, which determines the scale of the ratings error, σ_ϕ, only the location remains to be fixed. The location is identified by not including a constant term in the equation determining R_{ik}^*, the importance of attribute k to individual i, in (5.16).

5.3.4 Estimation

Across the different choice situations, the choices of individual i are independent conditional on β_i and T_{is}. Thus the conditional probability to choose J(i,1),…,J(i,S) for individual i with choice situations s=1,…,S, given β_i and T_{is}, is:

$$LC_i(\beta_i, T_{is}) = \prod_{s=1}^{S} P_{is}(J(i,s) \mid \beta_i, T_{is}) \tag{5.17}$$

with the choice probabilities as given in (5.13).

Moreover, conditional on β_i (or u_i) and T_{is} (or ε_{is}), the answers to the choice questions, the attribute consideration questions, and the attribute rating questions are independent of each other. Thus the likelihood $L_i(\beta_i,T_{is})$ of the responses to all of the questions faced by individual i, conditional on β_i and T_{is}, can be written as the product of the conditional likelihood contribution of each separate question:

(5.18) $$L_i(\beta_i,T_{is}) = LC_i(\beta_i,T_{is})\, G_i(\beta_i,T_{is})$$

where $G_i(\beta_i,T_{is})$ is the contribution of the individuals ratings and consideration sets information, which is a product of univariate normal probabilities (due to the independence, conditional on β_i and T_{is}).

$L_i(\beta_i,T_{is})$ is straightforward to compute. The unconditional likelihood is the expected value of this function over β_i and T_{is}, which can be approximated using simulations. This suggests that the model can be estimated with simulated maximum likelihood.[3] However, a problem arises from the fact that $LC_i(\beta_i,T_{is})$ is not a continuous function of the parameters, due to jumps in the choice probabilities where the consideration set changes. The discontinuities would greatly complicate the numerical procedure for finding the maximum. To circumvent this problem, we should avoid conditioning on T_{is}[4]. To see how this works, write the likelihood contribution of respondent i as

(5.19) $$L_i = E\{L_i(\beta_i,\varepsilon_{is})\} = E\{LC_i(\beta_i,\varepsilon_{is})\, G_i(\beta_i,\varepsilon_{is})\} = E\{E\{LC_i(\beta_i,\varepsilon_{is})\, G_i(\beta_i,\varepsilon_{is})|\, \beta_i\, \}\}$$

Conditioning on T_{is} is equivalent to conditioning on ε_{is}. Thus $L_i(\beta_i,\varepsilon_{is}) = L_i(\beta_i,T_{is})$, $LC_i(\beta_i,\varepsilon_{is}) = LC_i(\beta_i,T_{is})$ and $G_i(\beta_i,\varepsilon_{is}) = G_i(\beta_i,T_{is})$. For given β_i, the function $LC_i(\beta_i,\varepsilon_{is})$ is piecewise constant as a function of ε_{is}. The number of different values is at most $(S\times K)$, since, for given β_i the $\Delta U_{ik}(s)$ terms are also given, and the value of $LC_i(\beta_i,\varepsilon_{is})$ only changes if ε_{is} crosses one of the $(S\times K)$ terms $\Delta U_{ik}(s)\text{-}Z\gamma$. Denote the intervals on which $LC_i(\beta_i,\varepsilon_{is})$ is constant by I_q, $q = 1,\ldots,Q$ and the corresponding values of $LC_i(\beta_i,\varepsilon_{is})$ as $LC_i(q)$. (All this will depend on β_i (and γ); we do not explicitly mention that in the notation.) We can write the inner expectation as

(5.20) $$E\{LC_i(\beta_i,\varepsilon_{is})\, G_i(\beta_i,\varepsilon_{is})|\, \beta_i\} = LC_i(q)\, P(\varepsilon_{is}\in I_q\, |\beta_i)\, E\{G_i(\beta_i,\varepsilon_{is})|\, \beta_i,\varepsilon_{is}\in I_q\}$$

The probabilities $P(\varepsilon_{is}\in I_q\, |\beta_i)$ are simple univariate normal probabilities. The expected values $E\{G(\beta_i,\varepsilon_{is})|\beta_i,\varepsilon_{is}\in I_q\}$ can be estimated by a simulated mean, using draws from the conditional

[3] See, for example, the survey of Hajivassiliou and Ruud (1994) for properties of simulated maximum likelihood estimators.

[4] The procedure is similar to the way to tackle the same problem in a multinomial probit model, where a crude frequency simulator would lead to discontinuities.

distribution of ε_{is} given that $\varepsilon_{is} \in I_q$. The result is a simulation-based approximation that is continuous in the parameters, since $G_i(\beta_i,\varepsilon_{is})$ is continuous in the parameters. Drawing from the conditional (normal) distribution works as follows:

- denote the distribution function of the conditional distribution of ε_{is} given $\varepsilon_{is} \in I_q$ by F_q. Denote the inverse of F_q by $F_q^{-1}: (0,1) \rightarrow I_q$. If I_q is the interval [a,b], then for $t \in I_q$, $F_q(t)$ is given by $F_q(t) = (F_\varepsilon(b)-F_\varepsilon(a))^{-1}(F_\varepsilon(t)-F_\varepsilon(a))$, where $F_\varepsilon(t)$ is the (unconditional) distribution function of ε_{is}.
- draw d from U(0,1) (the uniform distribution)
- $\varepsilon_{is} = F_q^{-1}(d)$ is a draw from the conditional distribution of ε_{is} given $\varepsilon_{is} \in I_q$.

The outer expectation in the likelihood can be approximated by a simulated mean by drawing β_i. Thus the simulated likelihood approximation consists of draws of β_i as well as ε_{is}, but the two are separated and play a different role. As long as the distribution of ε_{is} is continuous, this procedure will lead to a continuous approximate likelihood. As the number of draws of both β_i and ε_{is} approach infinity the approximate likelihood approaches the true unconditional likelihood. In practice, this procedure will be more time consuming than other, more standard, simulated maximum likelihood estimators, since we need draws of ε_{is} for each draw of β_i. To keep computing time within acceptable limits, we have worked with 20 draws for β_i and 20 draws for ε_{is}, leading to 400 draws for each respondent.

5.4 Empirical Analysis

5.4.1 Data Description

The survey used for the empirical application was designed to examine whether consumers use all attribute information when making choices, and, if not, to enable identification of which attributes are employed. The main subject of the survey was a choice between restaurants each described by up to 12 attributes (restaurant type, price, menu, style, number of guests, dessert menu, independent bar, opening times, available methods of payment, distance from available parking, available seating places, and level of service). In the introduction to the survey, respondents were asked to imagine that they were having a weekend holiday in The Netherlands. The town they were visiting was unfamiliar to them and they had to decide where to eat in the town on a Saturday night. The survey was sent out to members of the CentER*data* consumer panel, consisting of a cross-section of households throughout The Netherlands. The panel is administered through Tilburg University for research purposes. From the 1535 people surveyed, 1465 usable questionnaires were obtained.

Table 5.1: Attributes and levels used in the experiment

Attribute	*Base*	*Level 1*	*Level 2*	*Extra Level*
Restaurant type	Small Restaurant	Restaurant	Hotel-Restaurant	Hotel-Restaurant
Average price of entrée	\$ 8	\$ 10	\$ 15	\$ 20
Menu	Basic Menu	Occasionally altered	Extensive	Very extensive
Style	Business	Modern	Old-fashioned	Very old-fashioned
Number of guests	Reasonably busy	Quiet	Reasonably busy	Very busy
Dessert menu	Only Ice-cream	Occasionally altered	Extensive	Very extensive
Separate bar area	Yes	Yes	No	-
Closing time	9 pm	10.30 pm	9 pm	-
Methods of Payment	Cash only	Cash, debit or credit card	Cash only	-
Parking	100 m away	In front of restaurant	300 m away	-
Seating available	Near entrance	Near window and inside		-
Personnel	Only owner working	A lot of personnel	Only a few personnel	-

The sample was divided into 6 groups with members of the same group receiving the same questionnaire, and different groups facing different sets of questions. The survey began with participants being presented a sequence of choice sets each containing 2 or 3 potential restaurants each described by a set of attributes, from the aforementioned list, and asked to indicate their preferred option. Each attribute was presented at a maximum of two levels in any one group. Table 5.1 presents the attributes and their levels. The choice profiles were designed using orthogonal fractional factorial designs following Green (1974). Orthogonal arrays offer a parsimonious method to assign the differing levels for each attribute to products while ensuring main-effect parameter estimation. All choice sets included a "base-alternative" which was constant across all choice sets for that group. Within each group all choice sets had identical dimensions. The choice sets presented to different groups differed in a number of ways; the number of restaurants in each choice set, the number of attributes, and the levels per attribute ('regular' difference, 'high' difference). The time taken to answer each choice set was recorded for all respondents. A summary of the choice questions asked of each group is provided in table 5.2.

Table 5.2: Description of choice sets per group

Group No.	*1*	*2*	*3*	*4*	*5*	*6*
No. of Products	2	2	2	2	2	3
No. of Attributes	6	6	3	12	12	6
No. of Choice Sets Faced	9	9	5	9	9	9
No. of Observations	100	100	100	100	100	100
Average Median Time per Question (sec)	11.43	12.63	10.28	21.44	19.40	17.24
Average No. of Attributes "Always Used"	2.60	2.62	1.77	4.52	4.50	2.79
Average No. of Attributes "Never Used"	2.21	1.91	1.12	4.13	4.31	2.12
Average Attribute Rating	4.39	4.49	4.79	4.18	4.10	4.52

As can be seen in table 5.2, group 6 was the only group that had a choice set with 3 alternatives with the remaining groups having 2 alternatives to choose between. The restaurants in the choice sets for group 3, were described by 3 attributes. Groups 1, 2 and 6, were provided information on 6 attributes, while groups 4 and 5 faced choice sets in which alternatives were described by the full set of 12 attributes. All respondents had a total of 9 choice questions to answer, except for the members of group 3 who had only 5. For use in our empirical application 100 respondents were randomly selected from each group. The reason for not using the complete sample is that estimating the model described in section 5.3 would then require a prohibitive amount of computer time.

As a proxy for cognitive effort per individual, we use median response time per individual. The median time is used rather than all separate response times or the mean response time to remove any bias caused by effects such as learning and fatigue, which would be expected to respectively shorten and lengthen the decision time. The averages of the individual median response times were taken across all members within each group and are also presented in table 5.2. These averages are clearly related to the number of attributes and the number of products faced. The shortest average median time of 10.28 seconds was recorded for members of group 3 with only 3 attributes, while the longest times were recorded for groups 4 and 5 (21.44 and 19.40 seconds respectively) who faced 12 attributes. Although alternatives seen by groups 1, 2, and 6 were all described by 6 attributes, a significant drop can be seen between the average recorded for group 6 (17.24 seconds) and those recorded for groups 1 and 2 (11.43 and 12.63 seconds respectively). This drop comes as a consequence of the reduction in alternatives per choice set from 3 to 2.

As can be seen in table 5.1, while most attributes take on ordered values, some of the attributes can have three unordered values. For example, style can be business, modern or old-fashioned. In this case, the utility contribution of the attribute is not given by (5.1), but by a linear combination of two dummies for two of the three possible levels, with corresponding random coefficients. Thus preference for this type of attribute will be described by two random coefficients instead of one.

Attribute Specific Information

After the choice questions, respondents were firstly asked to indicate attributes they had used in every choice situation (referred to as "always used"). Following this they were asked to point out attributes that they did not consider in any choice situation (referred to as "never used"). The last task asked of the survey participants was to rate the importance of each of the attributes they had seen in their choice sets on a scale of 1 to 7. For each group separately, the average number of attributes individuals indicated they had "always used" and "never used" are shown in table 5.2, as well as the average rating received by the various attributes in each group. The number of attributes seen by the different groups had a clear impact on the scores of all three types of questions. As expected, if the number of attributes faced by a group increases, the number of attributes reported as either "always used" or "never used" also increases. The increase for "never used" tends to be larger than the increase for "always used". This is in line with the idea that people turn to simpler decision strategies when problems become more complex. Finally, the average importance rating across all attributes for each group falls as the number of attributes increases.

To illustrate how this additional attribute information and the consumer response times can provide insight into the consumer choice process the results of three ordinary least squares regressions are provided in table 5.3. The dependent variables for the three regressions are the number of attributes "always used", the number of attributes "never used", and the average attribute importance rating, respectively. The three regressions all have as the independent variables the median response time per individual, a constant term, and three dummy variables: one for group 3, the second for groups 4 and 5 together, and the third for group 6. The dummy variables are included to remove any bias caused by changes in choice set dimensions (see table 5.2).

In the first equation in table 5.3, the coefficient of the median response time per individual is positive and significant at the 5% level of significance, with a t-value of 2.24. This suggests that a positive relationship exists between response time and using more attributes. The negative sign of response time in the equation for the number of attributes "never used" supports this, although, this coefficient is not significant. The final regression in table 5.3 shows that an increase in median response time is positively related to the importance attribute ratings. The estimated coefficient is significant, with a t-value of 2.55. Again this is in line with the idea that more involved respondents who spend more time on their choices, tend to find it more important to use many attributes in their decision process.

These results help to us understand the working of the model in section 5.3. In the threshold equation (5.6) of the previous section, we expect a negative effect of response time. Thus an increase in response time should reduce the threshold value. Equations (5.14) and (5.15) imply that this should increase the probability of an attribute being "always used" and decrease the chance of it being "never used". This is in agreement with the findings of table 5.3. Moreover, equation (5.16) implies that a higher average attribute rating means that, on average, the $\Delta U_{ik}(s)$ terms will be higher. This will mean that more attributes are in the individual's consideration set for any particular choice situation. Considering more attributes means spending more time. This is confirmed by the third regression of table 5.3. We do not give this a structural interpretation in our model: we assume that response time does not enter the ratings in equation (5.16), so the correlation between response time and ratings is driven by preference heterogeneity in our model. Explicitly incorporating response time in (5.16) might be an interesting extension.

Table 5.3: Regressions of attribute information variables
vs. median response time per individual*

"Always Used"		**"Never Used"**		**Average Attribute Rating**	
Variable	*Estimates*	*Variable*	*Estimates*	*Variable*	*Estimates*
Constant	2.41	*Constant*	2.14	*Constant*	4.32
	(17.48)		(19.76)		(56.66)
Group 3	-0.81	*Group 3*	-0.95	*Group 3*	0.37
	(-4.37)		(-5.55)		(3.62)
Groups 4&5	1.76	*Groups 4&5*	2.21	*Groups 4&5*	-0.38
	(10.82)		(17.34)		(-4.32)
Group 6	0.10	*Group 6*	0.09	*Group 6*	0.03
	(0.50)		(0.52)		(0.289)
Median Response Time	0.02 (2.24)	*Median Response Time*	-0.01 (-1.10)	*Median Response Time*	0.01 (2.55)
N = 600 Observations $R^2 = 0.321$		N = 600 Observations $R^2 = 0.498$		N = 600 Observations $R^2 = 0.079$	

*t-values placed in parentheses under the estimated coefficients

5.4.2 Estimation Results

The estimation results for the complete model discussed in section 5.3 are presented in table 5.4. Parameter estimates as well as their respective t-values are presented. The top half of the table contains the estimates of the means of the distributions of random attribute coefficients in the left column, and the standard deviations associated with these (normal) distributions in the right column. Only one of the 16 mean parameters is not significantly different from zero. Confidence intervals for the standard deviations would exclude a zero standard deviation in

12 out of 16 cases, suggesting that unobserved heterogeneity plays a significant role for most of the attributes. The relative size of the standard deviations compared to the means, suggests

Table 5.4: Estimation results

Parameter	*Estimate*	*t-value*	*Parameter*	*Estimate*	*t-value*
Means of Random Coefficients (RC)			*RC Standard Deviations*		
β_{i1} – Restaurant type I	-0.723	-16.401	ω_1	0.170	4.707
β_{i2} – Restaurant type II	-0.740	-15.433	ω_2	0.261	7.702
β_{i3} – Price	-0.051	-17.487	ω_3	0.062	21.903
β_{i4} – Menu	0.778	27.020	ω_4	0.172	12.271
β_{i5} – Style I	0.761	18.337	ω_5	0.126	2.944
β_{i6} – Style II	0.284	6.243	ω_6	0.713	15.952
β_{i7} – Style III	0.123	1.410	ω_7	0.960	9.175
β_{i8} – No. of guests I	1.156	26.585	ω_8	0.038	1.228
β_{i9} – No. of guests II	-0.546	-5.905	ω_9	1.200	10.170
β_{i10} – Dessert Menu	0.308	19.582	ω_{10}	0.181	13.259
β_{i11} – Independent Bar	-0.549	-10.755	ω_{11}	0.059	0.924
β_{i12} – Opening Times	-1.022	-15.757	ω_{12}	0.002	0.034
β_{i13} – Methods of Payment	-0.873	-16.159	ω_{13}	0.233	4.037
β_{i14} – Distance to Parking	0.004	17.522	ω_{14}	0.001	3.685
β_{i15} – Available Seating	0.572	23.136	ω_{15}	0.060	1.311
β_{i16} – Available Seating	0.056	2.138	ω_{16}	0.600	19.720
Category Bounds			*Error Standard Deviations (SD)*		
m_1	0.167	17.643	σ_ϕ – SD Ratings Error	0.361	23.306
m_2	0.329	23.271			
m_3	0.494	26.368	σ_v – SD "Always Used" Error	0.802	14.174
m_4	0.724	27.426			
m_5	1.026	27.810	σ_w – SD "Never Used" Error	0.751	16.762
m_6	1.390	27.440			
Threshold Equation					
γ_1 Constant Term	0.426	7.972	σ_ε – SD Threshold Error	0.545	9.999
γ_2 Dummy for Group 3	0.014	5.517			
γ_3 Dummy for Groups 4&5	-0.045	-6.207			
γ_4 Dummy for Group 6	-0.009	-7.156			
γ_5 Time Coefficient	-0.002	-2.972			

that heterogeneity is also economically relevant. For instance, the mean price coefficient is significantly negative, but the results still imply that a substantial number of people attach little or no value to prices.[5] The middle panel of table 5.4 contains, on the left-hand side, the estimated category bounds for the attribute ratings. These are auxiliary parameters for the importance ratings and require no further interpretation. On the right hand side are the standard deviations of the errors associated with each type of reported supplementary attribute-specific information. These suggest that there is much more idiosyncratic noise in the answers to the questions on which attributes were "always used" and "never used" than in the importance ratings. All three standard deviations are quite precisely determined.

Finally, estimates for the threshold equation are presented in the bottom panel of the table. The coefficient on response time is negative, confirming our hypothesis that an increase in response time is associated with a lower threshold and a more effort-intensive choice strategy with more considered attributes. The constant term and the dummy variables are all significant suggesting that there are clear differences in thresholds between choice sets of different sizes that is not simply picked up by shifts in response time alone. The standard deviation for the random component in the threshold equation is estimated rather precisely, and bounded away from zero at any conventional significance level. It is of the same order of magnitude as the idiosyncratic reporting errors, and relatively large compared to the coefficients on the group dummies, indicating a high degree of unobserved heterogeneity in thresholds.

5.4.3 Interpreting the model

From table 5.4 it can be seen that the estimated parameters are in general significant and have the expected signs. Still, these numbers alone do not give us a great deal of insight into how the various components of the model interrelate. To interpret the working of the model, we have therefore performed some additional calculations.

[5] Due to our normality assumption, positive price effects are not excluded, and our estimates would imply that some 15% of all respondents have a positive price coefficient. It would be straightforward to change the distributional assumptions to exclude this. Revelt and Train (1999), for example, assume that the price coefficient is deterministic.

Table 5.5 contains some simple statistics concerning utility differentials due to some selected attributes. The results are based on the preference parameters in table 5.4, for the choice problems presented to group 1. The table includes the minimum ΔU_{ik}, the maximum ΔU_{ik} and the average ΔU_{ik} for each attribute. This information determines whether an attribute was "always used" or "never used" and the attribute ratings, respectively (see equations (5.14), (5.15) and (5.16)). The final column gives the probability that an attribute is in the consideration set for the average choice problem, based upon the average utility difference. Of the attributes presented here, the type of menu offered by the restaurant on average gives the highest contribution to the utility difference between products. Accordingly, it has the highest probability to be included in the consideration set. The "average" probability for this attribute is 0.88. On the other hand, price typically has a more modest contribution to the utility differential between products. Accordingly, price is included in the consideration set less often: the average probability is only 0.59. This result will be specific to the price differentials used in the survey questions, but the point we want to make here is the relation between preferences and consideration set. In contrast to, for example, many hierarchical models or Shugan's (1980) model, our model implies that the most important attributes in terms of contribution to utility difference between products, are also the attributes that are most often included in the consideration sets.

Table 5.5: Summary statistics for attributes seen by group 1

Attribute	*Average ΔU_{ik}*	*Maximum ΔU_{ik}*	*Minimum ΔU_{ik}*	*Probability used in 'average' choice set*
Type	0.73	0.74	0.72	0.71
Price	0.48	0.76	0.25	0.59
Menu	1.12	1.56	0.78	0.88
Style	0.55	0.76	0.28	0.68
No. of guests	0.64	1.16	0.00	0.66
Dessert Menu	0.44	0.62	0.31	0.52

Another way to gain a better feel for how the information on the use of attributes interacts with individuals' preference parameters is to look at the posterior distribution of the random coefficient for some attribute, given that the attribute is "always used" or "never used". This is similar to a procedure recently suggested by Revelt and Train (1999), who look at posteriors given certain choices. Unconditional (prior) distributions of the preference weights are updated to form conditional (posterior) distributions by incorporating the new information in a Bayesian manner.

To explain how the method works, imagine we wish to obtain the density of a particular random coefficient, say β_k, conditional on observed information y (on choice, use of attributes, importance of attributes, etc.), and the population parameters of the model, θ. Let $h(\beta_k|y,\theta)$ denote this conditional density, then by Bayes' rule,

$$(5.21) \qquad h(\beta_k \mid y,\theta) = \frac{P(y \mid \beta_k,\theta) \times g(\beta_k \mid \theta)}{P(y \mid \theta)}.$$

Here $g(\beta_k|\theta)$ is the unconditional distribution of β_k, $P(y|\beta_k,\theta)$ is the probability of observing y conditional on β_k, and $P(y|\theta)$ is the marginal probability of observing y, not knowing β_k. In our case, $g(\beta_k|\theta)$ is the density function for a normal random variable and is thus easily obtained. Moreover, $P(y|\beta_k,\theta)$ and $P(y_i|\theta)$ are also relatively simple to calculate: $P(y|\beta_k,\theta)$ follows immediately from equations such as (5.14), (5.15) or (5.16) (depending on the type of information contained in y). A simulation procedure very similar to the one discussed in subsection 5.3.4 can then be used to calculate $P(y|\beta_k,\theta)$ or $P(y_i|\theta)$, which are both expected values of $P(y|\beta,\theta)$, with the expectation taken over a subset or all of the components of β.

We use this method to illustrate how the supplementary attribute-specific information incorporated in our model influences the distributions of the attribute coefficients. We take a respondent from group 1 with a response time of 11.43 seconds (the average of the median response times for group 1). (Other respondents give qualitatively similar results). In figure 5.1, three distributions for the coefficient of 'menu' are provided, an attribute that tends to be quite important compared to other attributes as we saw in table 5.5. The middle distribution is the unconditional (normal) distribution for the menu attribute coefficient. For virtually everyone, the coefficient is positive. To the left of this is the distribution of the same coefficient for respondents who stated that they "never used" this attribute for any of the group 1 choice questions. For such people, the restaurant menu is less important than for the average respondent. On the other hand, if the individual said that the menu attribute was "always used" the predicted distribution shifts to the right. Since menu is an attribute that often tends to be used, the information that it is "always used" is not as strong as the information that it is "never used". This explains why the shift to the left in the latter case is larger than the shift to the right in the former case.

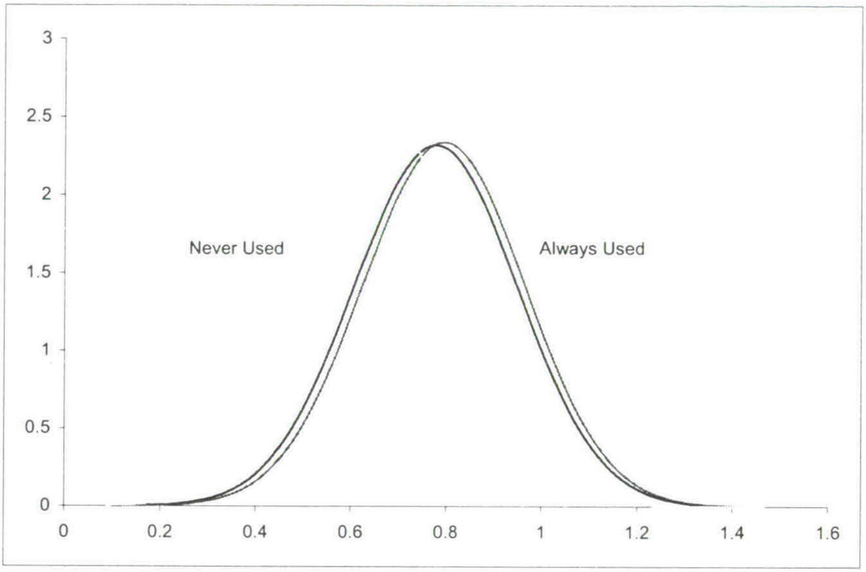

Figure 5.1: Distributions for the menu coefficient

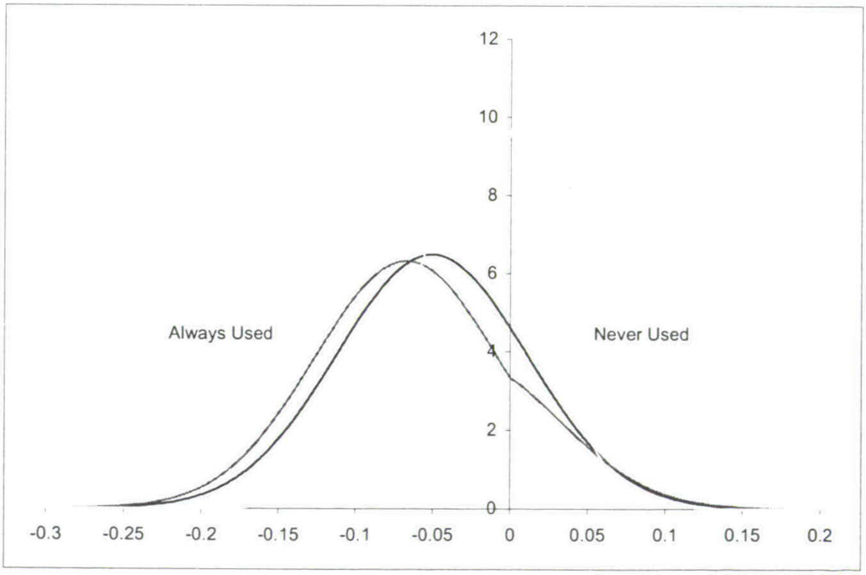

Figure 5.2: Distributions for the price coefficient

In figure 5.2, we present the same set of distributions for the price coefficient. The prior indicates that a substantial number of respondents would have a negative price coefficient, as discussed in the previous subsection. The conditional distributions move in opposite directions to those in figure 5.1 because the most of the density now lies below the origin. The information that price is "always used" moves the distribution further from zero, while the information that it is "never used" moves it closer to zero. In figure 5.2, the shift due to the information that the attribute is "always used", is larger than in figure 5.1. This corresponds to what we saw in table 5.5: price is less often used than menu, so that the fact that price is "always used" is more informative than the fact that menu is "always used".

Both conditional distributions exhibit a kink when they cross the origin. This is because the model works with the absolute change in utility, so it is the absolute value of the coefficient that matters in terms of it being considered or not. The unconditional distribution does not exhibit this kink because of its assumed normality.

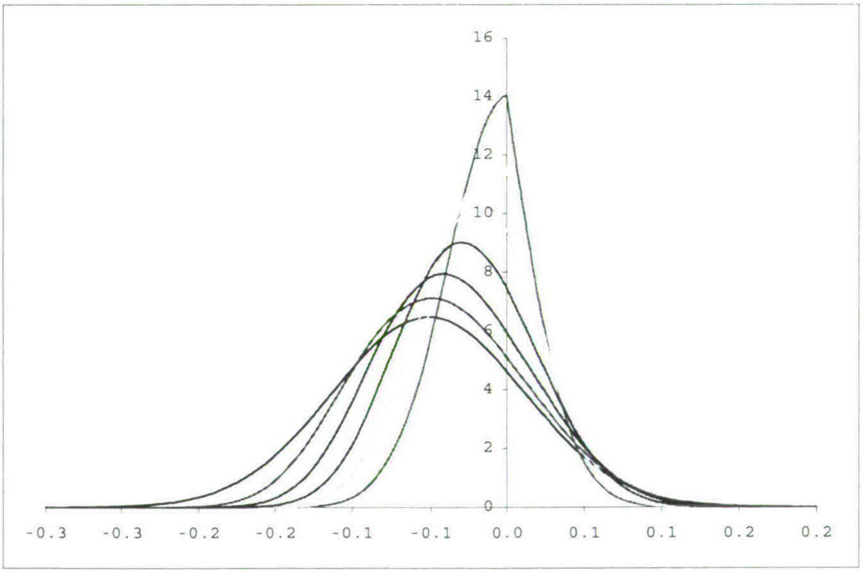

Figure 5.3: Distributions for the price coefficient given ratings are below a certain value

Figures 5.3 and 5.4 show what the attribute importance ratings for price say about the distribution of the price coefficient. The graphs shows the unconditional distribution of the price coefficient along with a series of distributions conditional on the knowledge that price received a rating below (figure 5.3) or above (figure 5.4) any given value between 1 and 7. Figure 5.3 shows how that the density shifts toward the origin if the information that price is unimportant becomes stronger, that is, as the information goes from "received a rating less than 7" to "received a rating less than 2". Conversely in figure 5.4, the conditional distributions move further away from the origin as we increase the observed lower limit for the introduced rating information, that is, as we provide stronger information that price is important.

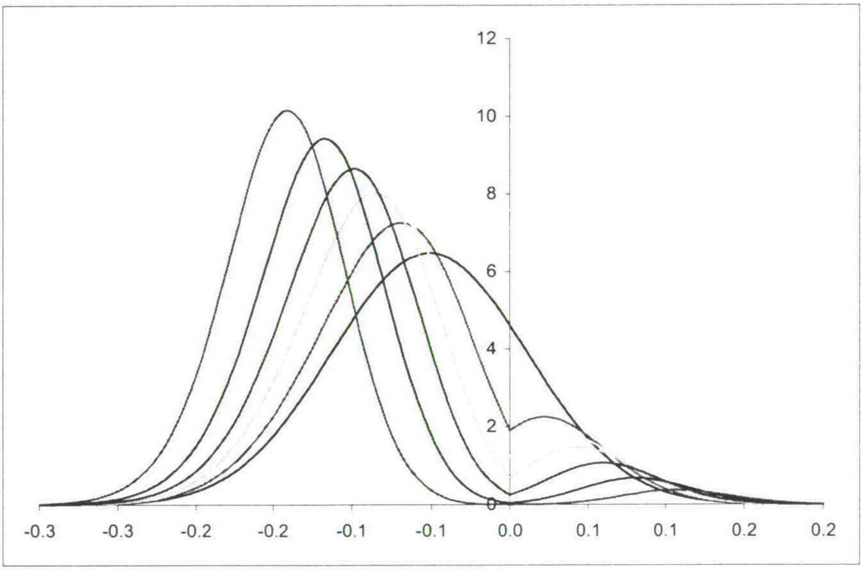

Figure 5.4: Distributions for the price coefficient given ratings are above a certain value

As a final illustration of how the model works we examine the conditional distribution of the threshold errors conditional on information on which attributes are used. Figure 5.5 shows the unconditional distribution for the threshold errors as well as the distributions conditional on two events: the individual stated that he/she used all attributes in the choice task, or the individual claimed to have used no attributes in the choice task. The unconditional distribution is the assumed mean zero normal distribution (see (5.12)). If the individual states that all attributes were used in making the choice decisions, the distribution for the threshold errors shifts to the left. In this case, the threshold for attribute consideration is much lower than for the population as a whole, implying that more attributes will be used. A shift in the opposite direction occurs when the information incorporated is that no attributes were used. Individuals providing this information will in general have higher thresholds than the average individual, implying that their choice strategy uses fewer attributes.

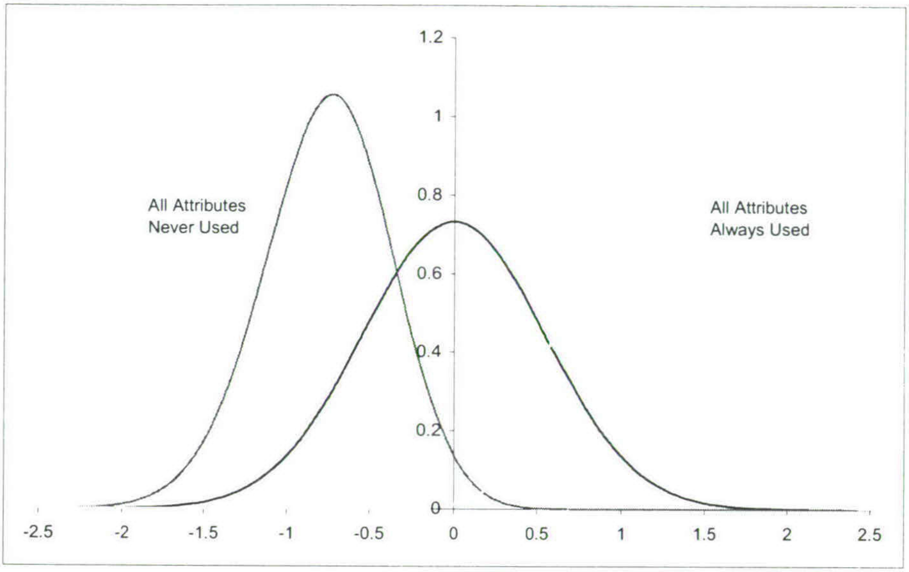

Figure 5.5: Threshold error distributions when all attributes are "always" or "never" used

5.5 Conclusion

This chapter has discussed an alternative to the standard fully compensatory model of consumer choice. Rather than assuming consumers have the ability or the desire to use all available information, this new specification incorporates the possibility that decision-makers do not consider all attributes. The standard fully compensatory model is nested within this framework which has consumers employing an attribute's information only if the difference in utility across the products in a choice set based on that particular attribute is above a threshold level. The model links the probability of an attribute being considered to both the preference weight an individual has for that attribute and the difference in attribute values seen for that attribute in the given choice context. A random coefficient specification is used, and along with the inclusion of heterogeneity in the thresholds, this allows for a wide variety of possible decision strategies.

With the incorporation of additional attribute specific information, the model was estimated on a set of consumer responses to a study of restaurant choice in The Netherlands, using a variant of the simulated maximum likelihood procedure. The results suggest there is significant heterogeneity across the population both in terms of individual attribute preferences as well as the individual threshold levels determining whether attributes are used. This heterogeneity suggests that there are significant differences across consumers in both which and how many attributes they consider in a given choice situation. Moreover, the thresholds in the model vary with both the complexity of the choice task, and the level of effort the respondent has put into the choice, measured by the individuals response time. We find that the probability that an attribute is considered increases with the individual's response time, confirming that consumers who spend more time on choices are using strategies closer to the fully compensatory decision process.

The model can be used to predict the probability that different attributes are used (see table 5.5) and the link between the change in utility for a given attribute can be seen to be clearly related to the predicted change in utility of that attribute. For example price which had an average utility difference of 0.48 is considered in about 59% of the choice sets, whereas the attribute menu with an average utility difference of 1.12 is predicted to have been used in about 88%.

The model is illustrated using a recent technique, developed by Revelt and Train (1999), for obtaining the distributions of model parameters conditional on certain information. This technique is used to demonstrate how the posterior distributions of random coefficients are affected by individual-specific information that the attributes were "always used" or "never used", or the importance rating of the attributes. Another illustration shows how the distribution for the threshold errors is altered by the information that all attributes were either "always used" or "never used", where it was shown that lower thresholds are expected in the former case and higher thresholds for the latter.

In summary, the proposal that individuals may not use a fully compensatory decision strategy, but rather may simplify choice tasks by considering only a limited number of attributes, is supported empirically. We find consumers typically do not use all attributes and that the number of attributes used is directly related to the response time or level of choice effort.

Chapter 6

Conclusion

This thesis has examined how consumers behave when making choice decisions. In particular, the research concentrates on examining the validity of the standard modelling assumption of a perfectly rational individual who evaluates products in a fully compensatory manner. Evidence suggesting that this assumption is inappropriate was presented and more behaviourally realistic models were proposed. In this final chapter of the thesis the main results of the research are summarised and suggestions for future research provided.

In chapter 2 the possibility that the complexity of a choice situation may affect the choice outcome is considered. The study analysed responses to a conjoint choice survey carried out by CentER*data* on consumer yoghurt choice in The Netherlands. In the survey complexity was deliberately manipulated so as to vary across the respondents. The survey was designed so that choice set complexity varied across the different questions. Initially a mixed logit model was employed to estimate consumer preferences for yoghurt while incorporating consumer heterogeneity. The underlying error term assumptions for this model, however, differed from those used in the standard models of discrete choice. Rather than assuming the unobserved inconsistencies were solely due to observational errors on behalf of the analyst, we now assumed that inconsistencies may also be due to mistakes on behalf of the respondent. To correct for the effect that differences in choice set complexity may have on choice accuracy the scale values of the generalised extreme value errors were allowed to differ across choice questions.

These estimates were then used to construct newly developed measures of choice set complexity following suggestions from the previous literature on consumer choice. The question of how to quantify the accuracy of an individual's choice response was also considered in this chapter and measures proposed. The basic hypothesis of the chapter was that if consumers are not perfectly rational utility maximisers, but rather come under the definition of boundedly rational individuals, increased task complexity should result in less accurate responses. This decrease in accuracy as complexity increases may come about in two ways. Firstly, it could be due to individuals making more errors as complexity increases while maintaining the same decision strategy, or alternatively, may be the result of consumers switching to simpler, though less accurate, decision rules in more difficult choice scenarios. The relationship between choice accuracy and choice set complexity was then estimated and found to be consistent with the idea that the accuracy of an individual's choice response has an inverse relationship with the complexity of the choice task. This result is consistent with the view of decision-makers as boundedly rational individuals, contradicting the standard modelling assumptions of a perfectly rational individual who has the ability to calculate completely and costlessly.

Future research in this area could examine how the complexity effects identified here vary across different segments of the population. For example, consumers who are more involved in the product class being analysed may be less prone to complexity effects. A similar result might be expected for more educated or intelligent people or for members of society who are more experienced in making such choices.

Chapter 3 developed a model to combine and compare consumer utility estimates based on stated preference ratings and choice responses. The same consumers were analysed using both types of preference data, thus if the models correctly captured consumer preferences, the preference estimates elicited using either data source should have been compatible. On the other hand, evidence of framing effects in economic decision-making is well established (Tversky and Kahneman, 1986) suggesting different task conditions may affect an individual's preferences. In a similar manner we expect task effects due to the difference in task conditions between the ratings and choice questions. To estimate consumer preferences from both data types simultaneously a new econometric model was provided where consumers' rating responses were modelled with a random coefficient ordered probit specification and a random coefficient logit framework was used to analyse the consumers' choices. In addition to allowing for preference heterogeneity across the population, the random coefficient specification introduced correlation between an individual's responses to both types of data. We allowed for a flexible monotonic transformation of utility between the choice and ratings contexts, by making the category bounds in the ordered probit free parameters to be estimated. Estimation and identification issues were discussed as well as potential efficiency gains over models considering the two data sets separately.

The basis for the empirical work in the chapter is the yoghurt survey analysed in chapter 2, however, now consumer ratings data were also incorporated. In our empirical results significant differences between ratings based and choice based utility estimates were found. In particular, respondents were relatively more price sensitive in the ratings tasks as well as more positive about possible new product extensions (i.e., recyclable packaging). These observed effects were in line with possible strategic behaviour by consumers in responding to the survey questions. Some support was found also for the prominence effect indicating that the most important attribute received greater weight in the choice task. While the mean parameters for the preference distributions differ, the correlation between random coefficients driving the two data sets was very strong.

Despite these differences in parameters it was found that the predictive ability of the different models were very similar. This finding may seem surprising, but is in line with earlier results by Dawes (1979) who showed that linear models perform very well in predicting the outcome of choice tasks even if the linear models are only directionally correct and the parameter values have incorrect values. Empirical results by Elrod et al. (1992) also illustrate a similar predictive ability of different model specifications based on consumer ratings and choice responses, further supporting the view that aggregate predictions are robust over utility measurement approaches.

Given that strategic response behaviour can explain part of the observed differences between ratings and choices in our estimates and the fact that choice tasks are less prone to strategic respondent behaviour, the results suggested that choice responses may be more suitable if one wishes to understand consumer preference structures. Carefully designed choice experiments can be used to avoid potential biases due to strategic behaviour. Further research in this area could explore consumers' inclination to respond strategically under different conditions (e.g., by changing the context presented in the study). Based on our findings future research may also address the possible value of combining ratings and choice responses in consumer segmentation research. For example, segmentation may be more successful if one takes into account the correlation in individuals' ratings and choice responses. The cost efficiency of collecting these two types of responses simultaneously may also be studied, trading off the costs of additional data collection per respondent against the costs of collecting data from more respondents. If the prediction of market shares is the objective however, collecting data in one response format may be equally suitable.

The evidence provided in chapters 2 and 3 suggested that the standard fully compensatory framework, which assumes a perfectly rational decision-maker, is inadequate as a description of the consumer choice process. The fourth chapter therefore provided a theoretical model of choice for a consumer who associates a positive cost with cognitive effort and trades-off the benefits and costs of employing mental resources when making a decision. This cost-benefit perspective provided potential for explaining why decision strategies vary across situations. The model extended previous consumer choice models in that the consumer not only chooses a product, but first decides how much effort to apply to a given choice problem. In the model, the optimal level of effort was determined by the consumer's cost of effort, the expected utility gain of a correct choice and the complexity of the choice set. The implications of the model were derived for the general case and were demonstrated numerically for a specific functional form. The model is not only consistent with many observations in the existing literature on consumer choice, but also provides insight into the underlying trade-offs that influence the decision process. In particular, the derived relationships between the level of effort applied in a choice situation and choice environment variables such as choice complexity and conflict were in line with prior research.

The empirical validity of the theoretical model was then explored with the use of a second survey that investigates hypothetical consumer restaurant choices in The Netherlands, and was also conducted by CentER*data*. In this survey response times were recorded for use as a proxy for consumer effort while consumer involvement measures were taken as proxies for individual differences in cost of effort and perceived complexity. Response time on each choice question was explained from the respondent specific consumer involvement measures, and from two choice task specific variables: the (estimated) utility difference between alternatives, and the number of elementary information processes (EIP's) of the choice problem. The results were found to be consistent with the theoretical model. For example, response time was found to increase with the consumer's interest and pleasure, which is in line with the notion that for very interested consumers, the cost of effort (compared to the expected utility gain of a correct choice) will be low. Effort was found to increase with both the utility difference and task complexity.

The results are encouraging and suggest that the model is able to capture important aspects of consumer decision strategies, however, there are also some clear limitations. The model has only been developed for the simple case of a choice between two products. A valuable extension would be to augment the range of choice situations for which the model is applicable by allowing consideration of choices between multiple products. In addition, the relationship between response time and various social demographics could provide insightful results. For example, the level of education may have an impact on the marginal cost of effort. The degree to which the results found here can be generalised to different product categories is also unknown. Finally, it would be interesting to examine to what extent functional form assumptions influence the model's behaviour and to test competing functional forms against real-world data.

In Chapter 5 a model was presented for the choice process of a boundedly rational individual. The model was based on the premise that rather than being perfectly rational with a perfect ability to calculate without cost, individuals are cognitive misers who prefer to use simplifying decision rules to avoid the complex fully compensatory decision rule. The strategy assumed the decision-maker processes the information in the choice set in two stages. In the initial stage the consumer decides upon which attributes are important enough to consider and in the second stage, alternatives are evaluated in a compensatory manner on these attributes alone. The model nests the fully compensatory choice process as a special case occurring only when an individual's consideration set of attributes is identical to the complete set of attributes available.

The mixed multinomial logit model formed the foundation of the model, however, we now incorporated the possibility that individuals base their choice on a limited number of product attributes only. Membership of the considered set of attributes was determined by whether the importance of an attribute in any particular choice situation lies above an individual's threshold level. An attribute's importance was determined by the absolute difference in utility between products in a choice situation due to that particular attribute. Thus, if there were higher differences in levels on that attribute, or the attribute has a higher worth to the individual, it will be more likely that the attribute was considered. The model allowed for heterogeneity in both individual preferences through random coefficients and for both structural and unobserved heterogeneity in the individual threshold values. Allowing for differences between individuals in this way allowed different individuals to employ many different choice processes (different attributes may have been considered as well as a different number of attributes).

The same data set as seen in the empirical analysis of Chapter 4 was used to implement the model, however, additional attribute-specific information was now also incorporated. This supplementary information was used to help identify individual choice strategies. An econometric model that incorporated both the choice data and the additional attribute-specific information was presented and a smooth simulated maximum likelihood procedure was introduced to obtain estimates of the model parameters. The estimation results suggest that higher response times (or higher effort) were associated with lower thresholds. This made sense as a lower threshold leads to consideration of more attributes. We also found that as choice complexity increased individuals increased the number of attributes they considered (lowered their thresholds). The estimation results and, in particular, the structural link between preference weights and whether or not attributes were considered in the choice decisions, were illustrated by comparing posterior distributions of the random coefficients given information on which attributes were and were not considered. This was similar to a recently developed method for obtaining the distributions of individual parameters conditional on their observed choices developed by Revelt and Train (1999).

It may be interesting to conduct further research to examine how social demographics or consumer involvement affect the choice process, the preference weights, and the threshold level. For example we may expect that more educated people and more involved consumers have lower thresholds so that they consider more attributes. Such individual characteristics might also affect the attribute ratings and the number of products always or never used. It would also be interesting to see whether the model is more applicable in choice sets with a small number of products described by a large number of attributes than in situations with a large number of choices described by a small number of attributes.

More generally this thesis has provided empirical evidence of bounded rationality as well as explaining and modelling such behaviour. The empirical work seen in the previous chapters, however, all relies on two stated preference or conjoint choice questionnaires; one for consumer yoghurt choice and one for choice of restaurants. Whether the results of this thesis are specific to the particular product categories chosen for the analysis or maybe be generalised to a wider range of choice contexts is yet to be examined. Furthermore, stated preference choice surveys are hypothetical in nature and thus may not adequately recreate the feeling of a real choice environment for a consumer. This may of course introduce a bias into the outcomes of the study. Therefore it would be worthwhile to see if the models can be estimated on revealed preference data sets which use real market data.

References

Abelson, R. P., and Levi, A. (1985), "Decision Making and Decision Theory," in: G. Lindzey and E. Aronson (eds.), *The Handbook of Social Psychology*, 1, New York: Random House.

Adamowicz, W. L., Louviere, J. J., and Williams, M. (1994), "Combining Stated and Revealed Preference Methods for Valuing Environmental Amenities," *Journal of Environmental Economics and Management*, 26, 271-276.

Allenby, G. M., and Ginter, J. L. (1995), "The Effects of In-store Displays and Feature Advertising on Consideration Sets," *International Journal of Research in Marketing*, 12, 67-80.

Andrews, C., Durvasala, S., and Akhter, S. (1990), "A Framework for Conceptualizing and Measuring the Involvement Construct in Advertising Research," *Journal of Advertising*, 19, 27-40.

Andrews, R. L., and Srinivasan, T. C. (1995), "Studying Consideration Effects in Empirical Choice Models Using Scanner Panel Data," *Journal of Marketing Research*, 12, 30-41.

Beatty, S., and Smith, S. (1987), "External Search Effort: An Investigation Across several Product Categories," *Journal of Consumer Research*, 14, 83-95.

Ben-Akiva, M., and Boccara, B. (1995), "Discrete Choice Models with Latent Choice Sets," *International Journal of Research in Marketing*, 12, 9-24.

Ben-Akiva, M., Morikawa T., and Shiroishi, F. (1992), "Analysis of the Reliability of Preference Ranking Data," *Journal Business of Research*, 24, 149-164.

Ben-Akiva, M., and Lerman, S. R. (1985), *Discrete Choice Analysis: Theory and Application to Travel Demand*, Cambridge, Mass: MIT Press.

Bettman, J. R., Johnson, E. J., and Payne, J. W. (1990), "A Componential Analysis of Cognitive Effort in Choice," *Organizational Behavior and Human Decision Processes*, 45, 111-139.

Bettman, J. R., Johnson, E. J., Luce, M. F., and Payne, J. W. (1993a), "Correlation, Conflict and Choice," *Journal of Experimental Psychological: Learning, Memory and Cognition*, 19, 931-951.

Bettman, J. R., Johnson, E. J., Luce, M. F., and Payne, J. W. (1993b), "Correlation, Choice and Conflict," *Journal of Experimental Psychological: Learning, Memory and Cognition*, 21, 167-184.

Bettman, J. R., Johnson E. J., and Payne, J. W. (1990), "A Computational Analysis of Cognitive Effort in Choice," *Organizational Behavior and Human Decision Processes* 45, 111-139.

Bettman, J. R., Johnson, E. J., Luce, M. F., and Payne, J. W. (1993), "Correlation, Conflict and Choice," *Journal of Experimental Psychological: Learning, Memory and Cognition*, 19, 931-950.

Billings, R. S., and Scherer, L. L. (1988), "The Effects of Response Mode and Importance on Decision-Making Strategies: Judgment Versus Choice," *Organizational Behavior and Human Decision Making Processes*, 41, 1-19.

Bloch, P., Sherrell, D., and Ridgway, N. (1986), "Consumer Search: An Extended Framework," *Journal of Consumer Research*, 13, 119-126.

Bloch, P., and Richins, M. (1983), "Shopping Without Purchase: An Investigation of Consumer Browsing Behavior," in: R. Bagozzi, and A. Tybout (eds.), *Advances in Consumer Research*, 10, Ann Arbor, MI: Association for Consumer Research, 313-318.

Bockenholt, U., Diterich, A., Aschenbrenner, M., and Schmalhofer, F. (1991), "The Effect of Attractiveness, Dominance, and Attribute Differences on Information Acquisition in Multiattribute Binary Choice," *Organizational Behavior and Human Decision Processes*, 49, 258-281.

Boxall, P. C., Adamowicz, W. L., Swait, J., Williams, M., and Louviere, J. J. (1996), "A Comparison of Stated Preference Methods for Environmental Valuation," *Ecological Economics*, 18, 243-253.

Boyle, K. J., Johnson, F. R., McCollum, D. W., Desvousges, W. H., Dunford, R. W., and Hudson, S. P. (1996), "Valuing Public Goods: Discrete Versus Contingent Valuation Responses," *Land Economics*, 72, 381-396.

Bradley, M., and Daley, A. (1994), "Use of the Logit Scaling Approach to Test Rank-Order and Fatigue Effects in Stated Preference Data," *Transportation*, 21, 167-184.

Bunch, D., and Batsell, R. (1989), "A Monte Carlo Comparison of Estimators for the Multinomial Logit Model," *Journal of Marketing Research*, 26, 56-68.

Busemeyer, J., and Townsend, J. (1993), "Decision Field Theory: A Dynamic-Cognitive Approach to Decision Making in an Uncertain Environment," *Psychological Review*, 100, 432-459.

Cameron, T. A., Poe, G. L., Ethier, R. G., and Schulze, W. D. (1999), "Alternative Nonmarket Value-Elicitation Methods: Are Revealed and Stated Preferences the Same?" Working Paper, Department of Economics, UCLA, December 1999.

Carson, R., Flores, N., Martin K., and Wright, J. (1996), "Contingent Valuation and Revealed Preference Methodologies: Comparing the Estimates of Quasi-Public goods," *Land Economics*, 72, 80-99.

Carson, R. T., Groves, T., and Machina, M. (1999), "Incentive and Informational Properties of Preference Questions," plenary adress European Association of Resource and Environmental Economists, Oslo, Norway, June 1999.

Celsi, R., and Olsen, J. (1988), "The Role of Involvement in Attention and Comprehension Processes," *Journal of Consumer Research*, 15, 210-224.

Celuch, K., and Evans, R. (1989), "An Analysis of the Convergent and Discriminant Validity of the Personal Involvement Inventory and the Consumer Involvement Profile," *Psychological Reports*, 65, 1291-1297.

Chaiken, S. (1980), "Heuristic Versus Systematic Information Processing and the Use of Source Versus Message Cues in Persuasion," *Journal of Personality and Social Psychology*, 39, 752-766.

Chiang, J., Chib, S., and Narasimhan, C. (1999), "Markov Chain Monte Carlo and Model of Consideration Set and Parameter Heterogeneity," *Journal of Econometrics*, 89, 223-248.

Clark, K., and Belk, R. (1979), "The Effects of Product Involvement and Task Definition on Anticipated Consumer Effort," in: W. Wilkie (ed.), *Advances in Consumer Research*, 6, Ann Arbor, MI: Association for Consumer Research, 313-318.

Conlon, B. J., Dellaert, B. G. C., and van Soest, A. (2000), "Combining and Comparing Consumers' Stated Preference Ratings and Choice Responses," *CentER Discussion Paper No. 119*, CentER for Economic Research, Tilburg University.

Conlon, B. J., Dellaert, B. G. C., and van Soest, A. (2001), "Optimal Effort in Consumer Choice," *CentER Discussion Paper No.* , CentER for Economic Research, Tilburg University.

Currim, I., Meyer, R., and Le, N. (1988), "Disaggregate Tree- Structured Modeling of Consumer Choice Data," *Journal of Marketing Research*, 25, 253-265.

Dawes, R. M. (1964), "Social Selection Based on Multidimensional Choice," *Journal of Abnormal and Social Psychology*, 68, 104-109.

Dawes, R. M. (1979), "The Robust Beauty of Improper Linear Models in Decision Making," *American Psychologist*, 34, 571-582.

Dellaert, B. G. C., Brazell, J. D., and Louviere, J. J. (1999), "The Effect of Attribute Variation on Consumer Choice Consistency," *Marketing Letters*, 10, 139-147.

de Palma, A., Myers, G. M., and Papageorgiou Y. Y. (1994), "Rational Choice Under an Imperfect Ability to Choose," *American Economic Review*, 84, 419-440.

Dimanche, F., Havits, M., and Howard, D. (1991), "Testing the Involvement Profile (IP) Scale in the Context of Selected Recreational and Touristic Activities," *Journal of Leisure Research*, 23, 51-66.

Einhorn, H. J., Kleinmuntz, D. N., and Kleinmuntz, B. (1979), "Linear regression and process tracing models of judgment," *Psychological Review*, 86, 465-485.

Elrod, T., Louviere J. J., and Davey, K. S. (1992), "An Empirical Comparison of Ratings-Based and Choice-Based Conjoint Models," *Journal of Marketing Research*, 29, 368-377.

Espinoza-Varas, B., and Watson, C. (1994), "Effects of Decision Criterion on Response Latencies of Binary Decisions," *Perception and Psychophysics*, 55, 190-203.

Fader, P. S., and McAlister, L. (1990), "An Elimination by Aspects Model of Consumer Response to Promotion Calibrated on UPC Scanner Data," *Journal of Marketing Research*, 27, 322-332.

Fischer, G. W., Luce, M. F., and Jia, J. (2000), "Attribute Conflict and Preference Uncertainty: Effects of Judgment Time and Error," *Management Science*, 46, 88-103.

Gensch, D., and Javalgi, R. (1987), "The Influence of Involvement on Disaggregate Attribute Choice Models," *Journal of Consumer Research*, 14, 71-82.

Gensch, D. (1987), "A Two-Stage Disaggregate Attribute Choice Model," *Marketing Science*, 6, 223-239.

Gensch, D. H., and Ghose, S. (1992), "Elimination by Dimensions," *Journal of Marketing Research*, 29, 417-429.

Gensch, D. H., and Ghose, S. (1997), "Improving PRETREE's Predictive Capabilities," *European Journal of Operations Research*, 97, 465-479.

Gensch, D., and Svestka, J. (1979), "An Exact Hierarchical Algorithm for Determining Aggregate Statistics from Individual Choice Data," *Management Science*, 25, 939-952.

Gensch, D., and Svestka, J. (1984), "A Maximum Likelihood Hierarchical Disaggregate Model for Predicting Choices of Individuals," *Journal of Mathematical Psychology*, 28, 160-178.

Goldsmith, R., and Emmert, J. (1991), "Measuring Product Category Involvement: A Multitrait-Multimethod Study," *Journal of Business Research*, 23, 363-371.

Green, P. E. (1974), "On the Design of Choice Experiments Involving Multifactor Alternatives," *Journal of Consumer Research*, 1, 61-68.

Grether, D., and Wilde, L. (1984), "An Analysis of Conjunctive Choice: Theory and Experiments," *Journal of Consumer Research*, 10, 373-385.

Haaijer, R., Kamakura, W., and Wedel, M. (2000), "Response Latencies in the Analysis of Conjoint Choice Experiments," *Journal of Marketing Research*, 37, 376-382.

Haaijer, R., Wedel, M., Vriens, M., and Wansbeek, T. (1998), "Utility Covariances and Context Effects in Conjoint MNP Models," *Marketing Science*, 17, 236-252.

Hajivassiliou, V.A., and Ruud, P.A. (1994), "Classical Estimation Methods for LDV Models Using Simulation," in: R. F. Engle, and D. L. McFadden (eds.), *Handbook of Econometrics*, Amsterdam: North Holland, 2384-2438.

Hausman, J. (1978), "Specification Tests in Econometrics," *Econometrica*, 46, 1251-1271.

Hendrick, C., Mills, J., and Kiesler, C. (1968), "Decision Time as a Function of the Number and Complexity of Equally Attractive Alternatives," *Journal of Personality and Social Psychology*, 8, 313-318.

Hensher, D. A., and Bradley, M. (1993), "Using Stated Preference Response Data to Enrich Revealed Preference Discrete Choice Models," *Marketing Letters*, 4, 39-152.

Hensher, D. A., Louviere J. J., and Swait, J. (1999), "Combining Sources of Preference Data," *Journal of Econometrics*, 89, 197-221.

Huber, O. (1980), "The Influence of Some Task Variables in an Information- Processing Decision Model," *Acta Psychologica*, 45, 187-196.

Huber, J., and Klein, N. (1991), "Adapting Cutoffs to the Choice Environment: The Effects of Attribute Correlation and Reliability," *Journal of Consumer Research*, 18, 346-357.

Huber, J., and Zwerina, K. (1996), "The Importance of Utility Balance in Efficient Choice Designs," *Journal of Marketing Research*, 33, 307-317.

Hutchison, W., Raman, K., and Mantrala, M. (1994), "Finding Choice Alternatives in Memory: Probability Models of Brand Name Recall," *Journal of Marketing Research*, 31, 441-461.

Johnson, E. J., and Payne, J. W. (1985), "Effort and Accuracy in Choice," *Marketing Science*, 31, 395-414.

Johnson, E. J. (1979), "Deciding How To Decide: The Effort of Making a Decision," Unpublished Manuscript, University of Chicago.

Johnson, E. J., and Payne, J.W. (1985), "Effort and Accuracy in Choice," *Marketing Science*, 31, 395-414.

Johnson, E. J., Meyer, R. J., and Ghose, S. (1989), "When Choice Models Fail: Compensatory Models in Negatively Correlated Environments," *Journal of Marketing Research*,24, 255-270.

Kiesler, C. A. (1966), "Conflict and Number of Choice Alternatives," *Psychological Reports*, 18, 603-610.

Klein, N., and Bither, S. (1987), "An Investigation of Utility-Directed Cutoff Selection," *Journal of Consumer Research*, 14, 240-256.

Laurent, G., and Kapferer, J. (1985), "Measuring Consumer Involvement Profiles," *Journal of Marketing Research*, 22, 41-53.

Link, S. (1975), "The Relative Judgment Theory of Two Choice Response Times," *Journal of Mathematical Psychology*, 12,114-135.

Louviere, J. J. (1995), "Relating Stated Preferences Measures and Models to Choices in real Markets: Calibration of CV Responses," in D. J. Bjornstad, and J. R. Kahn (eds.), *The*

Contingent Valuation of Environmental Resources, Brookfield: Edward Elgar, 167-188.

Louviere, J. J. (1994), "Conjoint Analysis," in: R. Bagozzi, (ed.), *Advanced Methods of Marketing Research*, Blackwell Publishers, Cambridge, MA, 223-259.

Louviere, J. J., Fox, M. F., and Moore, W. L. (1993), "Cross-Task Validity Comparisons of Stated Preference Choice Models," *Marketing Letters*, 4, 205-213.

Louviere, J. J., Meyer, R. J., Bunch, D. S., Carson, R., Dellaert, B. G. C., Hanemann, W. M., Hensher, D., and Irwin, J. (1999), "Combining Sources of Preference Data for Modeling Complex Decision Processes," *Marketing Letters*, 10, 205-217.

Louviere, J., J., and Woodworth, G. (1983), "Design and Analysis of Simulated Consumer Choice or Allocation Experiments: An approach Based on Aggregate Data," *Journal of Marketing Research*, 20, 350-367.

Manrai, A., and Sinha, P. (1989), "Elimination-by-Cutoffs," *Marketing Science*, 8, 133-152.

McFadden, D. (1986), "The Choice Theory Approach to Market Research," *Marketing Science*, 5, 275-297

McFadden, D., and Train, K. (2000), "Mixed Logit Models for Discrete Response," *Journal of Applied Econometrics*, 15, 447-470.

Mittal, B. (1995), "A Comparative Analysis of Four Scale of Consumer Involvement," *Psychology and Marketing*, 12, 663-682.

Mittal, B., and Lee, M. (1989), "A Causal Model of Consumer Involvement," *Journal of Economic Psychology*, 10, 363-389.

Montgomery, H., Selart, M., Garling T., and Lindberg E. (1988), "Adaptive Strategy Selection in Decision Making," *Journal of Experimental Psychology: Learning, Memory and Cognition*, 14, 534-552.

Moore, W. L., and Lehmann, D. R. (1980), "Individual Differences in Search Behavior for a Nondurable," *Journal of Consumer Research*, 7, 296-307.

Morikawa, T. (1989), "Incorporating Stated Preference Data in Travel Demand Analysis," Ph.D. Dissertation, Dept. of Civil Engineering, MIT.

Newell, A., and Simon, H. (1972), *Human Problem Solving*, Prentice-Hall, Englewood Cliffs, N. J.

Olsen, G. D., Swait, J., Johnson, R. D., and Louviere, J. J. (1995), "Response Mode Influences on Attribute Weight and Predictive Ability When Linear Models are Not Certain to be Robust," Working Paper, Faculty of Management, University of Calgary.

Payne, J. W. (1982), "Contingent Decision Behavior," *Psychological Bulletin*, 92, 382-402.

Payne, J. W., Bettman, J. R., and Johnson, E. J. (1988), "Adaptive Strategy Selection in Decision Making," *Journal of Experimental Psychology: Learning Memory and Cognition*, 14, 534-552.

Payne, J. W., Bettman, J. R., and Johnson, E. J. (1992), "Behavioral Decision Research: A Constructive Processing Perspective," *Annual Review of Psychology*, 43, 87-131.

Payne, J. W., Bettman, J. R., and Johnson, E. J. (1993), *The Adaptive Decision Maker*, New York: Cambridge University Press.

Park, W., and Parker Lessig, V. (1981), "Familiarity and Its Impact on Consumer Decision Biases and Heuristics," *Journal of Consumer Research*, 8, 223-230.

Petty, R., and Cacioppo, J. (1986), "The Elaboration Likelihood Model of Persuasion," in: L. Berkowitz (ed.), *Advances in Experimental Psychology*, NewYork: Academic Press, 668-672.

Poiesz, T., and De Bont, C. (1995), "Do We Need Involvement to Understand Consumer Behavior?" *Advances in Consumer Research*, 22, 448-452.

Pollay, R. (1970a), "The Structure of Executive Decisions and Decision Times," *Administrative Science Quarterly*, 15, 459-471.

Pollay, R. (1970b), "A Model of Decision Times in Difficult Decision Situations," *Psychological Review*, 77, 274-281.

Pratkanis, A., and Greenwald, A. (1993), "Consumer Involvement, Message Attention, and the Persistence of Persuasion Impact in a Message-Dense Environment. Special Issue: Involvement," *Psychology and Marketing*, 10, 321-332.

Revelt, D., and Train, K. (1999), "Customer-Specific Taste Parameters and Mixed Logit: Households' Choice of Electricity Supplier," *Economics Working Paper No. 274*, Department of Economics, University of California at Berkeley.

Roberts, J. H., and Lattin, J. M. (1991), "Development and Testing of a Model of Consideration Set Composition," *Journal of Marketing Research*, 28, 429-440.

Rodgers, W., and Schneider, K. (1993), "An Empirical Evaluation of the Kapferer-Laurent Consumer Involvement Profile Scale," *Special Issue: Involvement, Psychology and Marketing*, 10, 333-345.

Rubinstein, A. (1998), *Modelling Bounded Rationality*, Cambridge, Massachusetts: MIT Press.

Russo, J. E., and Dosher, B. A. (1983), "Strategies for Multiattribute Binary Choice," *Journal of Experimental Psychology: Learning, Memory and Recognition*, 9, 676-696.

Schoemaker, P. (1982), "The Expected Utility Model: Its Variants, Purposes, Evidence and Limitations," *Journal of Economic Literature*, 20, 529-563.

Sergent, J., and Takane, Y. (1987), "Structures in Two-Choice Reaction-Time Data," *Journal of Experimental Psychology*, 13, 300-315.

Sethuraman, R., Cole, C., and Jain, D. (1994), "Analyzing the Effect of Information Format and Task on Cutoff Search Strategies," *Journal of Consumer Psychology*, 3, 103-136.

Shugan, S. (1980), "The Cost of Thinking," *Journal of Consumer Research*, 7, 99-111.

Simon, H. A. (1955), "A Behavioral Model of Rational Choice," *Quarterly Journal of Economics*, 69, 99-118.

Stone, M. (1960), "Models of Choice-Reaction Time," *Psychometrika*, 25, 251-260.

Swait, J. (2000), "A Non-Compensatory, Choice Model Incorporating Attribute Cutoffs," *Transportation Research B*, (Forthcoming).

Swait, J., and Adamowicz, W. (2000), "Choice Environment, Market Complexity, and Consumer Behavior: A Theoretical and Empirical Approach for Incorporating Decision Complexity into Models of Consumer Choice," *Organizational Behavior and Human Decision Making*, forthcoming.

Swait, J., and Adamowicz, W. (2001), "The Influence of Task Complexity on Consumer Choice: A Latent Class Model of Decision Strategy Switching," *Journal of Consumer Research*, (Forthcoming).

Swait, J., and Ben-Akiva, M. (1987a), "Incorporating Random Constraints in Discrete Choice Models of Choice Set Generation," *Transportation Research B*, 21, 91-102.

Swait, J., and Ben-Akiva, M. (1987b), "Empirical Test of a Constrained Choice Discrete Model: Mode Choice in Sao Paulo, Brazil," *Transportation Research B*, 21, 103-115.

Swait, J., and Louviere, J. J. (1993), "The Role of the Scale Parameter in the Estimation and Comparison of Multinomial Logit Models," *Journal of Marketing Research*, 30, 305-314.

Swait, J., Louviere, J. J., and Williams, M. (1994), "A Sequential Approach to Exploiting the Combined Strengths of SP and RP Data: Application to Freight Shipper Choice," *Transportation*, 21, 135-152.

Takane, Y., and Sergent, J. (1983), "Multidimensional Scaling Models for Reaction Times and Same-Different Judgments," *Psychometrika*, 48, 393-423.

Tversky, A. (1969), "Intransitivities of Preferences," Psychological Review, 84, 327-352.

Tversky, A. (1972), "Elimination by Aspects: A Theory of Choice," *Psychological Review*, 79, 281-299.

Tversky, A., and Sattah, S. (1979), "Preference Trees," *Psychological Review*, 86, 542-573.

Tversky, A., and Kahneman, D. (1986), "Rational Choice and the Framing of Decisions," *Journal of Business*, 59, 251-278.

Tversky, A., Sattath S., and Slovic, P. (1988), "Contingent Weighting in Judgment and Choice," *Psychological Review*, 95, 371-384.

Tyebjee, T. (1979), "Response Time, Conflict and Involvement in Brand Choice," *Journal of Consumer Research*, 6, 295-304.

Wittink, D. R., and Cattin, P. (1989), "Commercial Use of Conjoint Analysis: An Update," *Journal of Marketing*, 53, 91-96.

Wright, P. (1975), "Consumer Choice Strategies: Simplifying vs. Optimizing," *Journal of Marketing Research*, 12, 60-67.

Samenvatting

(Summary in Dutch)

Een belangrijk onderzoeksterrein binnen de marketing is onderzoek naar de voorkeuren van consumenten en welke keuzeprocessen consumenten gebruiken. Een goed begrip van consumentenkeuzegedrag kan namelijk leiden tot significante verbeteringen in produkt of service design, prijsstrategie, distributiekanalen, de selectie van communicatiestrategieën, en kan ook van invloed zijn op de uitkomsten van maatschappelijke welvaartanalyses. De meest gebruikte methode om consumentenvoorkeur in beeld te brengen is het multi-attribuut keuzemodel. Het vermogen van deze modellen om keuzeverdelingen te voorspellen en diagnostische informatie te verschaffen stelt de onderzoeker in staat om de gedragsprocessen, die ten grondslag liggen aan de keuzen beter te begrijpen. Hierdoor vormen multi-attribuut keuzemodellen niet alleen voor marketing een relevante benadering maar ook voor een breed scala aan andere disciplines zoals psychologie, economie, management en verkeerskunde.

Multi-attribuut keuzemodellen kunnen gebaseerd zijn op verschillende structurele modellen, kunnen voor verschillende doeleinden worden gebruikt en ook op verschillende veronderstellingen zijn gebaseerd. De meeste huidige modellen gaan uit van een volledig rationeel nutmaximalizerend individu dat het economisch nut van een produkt bepaalt door gelijktijdig alle produktattributen te evalueren. Hierbij wordt het relatieve nut van ieder attribuut gewogen en opgeteld tot een totaal produktnut zodanig dat de attributen elkaar kunnen compenseren. Er bestaan echter onderzoeksresultaten die suggereren dat het gedrag van consumenten vaak niet binnnen dit geïdealiseerde raamwerk past. Het doel van dit proefschrift is daarom om ons vermogen om keuzegedrag van mensen te begrijpen verder uit te bouwen door afwijkingen van rationeel nutmaximaliserend gedrag te modelleren en verklaren. In het bijzonder worden modellen ontwikkeld die het mogelijk maken om gedrag gekarakteriseerd door beperkte rationaliteit op te nemen. Deze modellen worden getoetst en er wordt empirisch bewijs aangedragen dat de voorgestelde modellen ondersteunt.

In hoofdstuk 2 beginnen we met een analyse van de mogelijkheid dat individuele keuzeprocessen worden beïnvloed door de complexiteit van de keuzetaak. De veronderstelling van perfecte rationaliteit impliceert dat de beslisser over de benodigde vaardigheden beschikt om elke gewenste complexe calculatie uit te voeren om zijn of haar optimale keuzealternatief te bepalen, en dat deze calculaties zonder enige kosten of moeite kunnen worden verricht. In een dergelijke situatie zou de complexiteit van de keuzeset geen rol moeten spelen in het keuzeproces. Rekening houdend met de mogelijkheid van beperkte rationaliteit bij de consumenten zouden we echter verwachten dat hogere niveaus van complexiteit samenhangen met meer fouten in de consumentenbeslissingen.

Om deze relatie tussen keuzetaakcomplexiteit en de nauwkeurigheid van keuzes te analyseren maken we gebruik van een conjuncte keuzeanalyse ten aanzien van yoghurtprodukten. Deze gegevens zijn verzameld door CentER*data* bij een groot Nederlands consumentenpanel. We schatten een mixed logit model met behulp van de Simulated Maximum Likelihood benadering, waarin random coëfficiënten de niet geobserveerde heterogeniteit opvangen, terwijl de resterende fouttermen worden geïnterpreteerd als keuzefouten. Van deze laatste fouttermen word verondersteld dat ze onafhankelijk en identiek zijn verdeeld. De variantie van deze fouttermen is vraagspecificiek gemodelleerd, zodat mogelijk effecten van keuzetaakcomplexiteit op de omvang van de foutterm kunnen worden meegenomen. Twee nieuwe maten voor keuzenauwkeurigheid worden gedefinieerd en vervolgens berekend op basis van de schattingen uit deze mixed logit benadering.

Hoofdstuk 2 stelt ook een aanpak voor om de complexiteit van een gegeven keuzesituatie te meten op basis van dezelfde mixed logit parameter schattingen. In een regressie-analyse worden vervolgens de nauwkeurigheidsmaten uitgezet tegen de keuzecomplexiteitsvariabelen. Het blijkt dat de keuzenauwkeurigheid significant wordt beïnvloed door complexiteit gemeten in termen van attribuut variatie binnen alternatieven, de covariantie van de attributen tussen alternatieven en het verschil in nut tussen produkten. De richting van de geschatte effecten komt overeen met eerdere voorspellingen in de literatuur. Het hoofdstuk biedt hiermee een duidelijk bewijs voor complexiteiteffecten in het keuzegedrag van consumenten. Ons resultaat wijst erop dat beslissers beter beschreven kunnen worden met een model voor beperkt rationeel gedrag dan door een model gebaseerd op volledige rationaliteit.

Het tweede essay (hoofdstuk 3) onderzoekt de vraag hoe twee verschillende typen gegevens (keuzes en preferenties) verzameld bij dezelfde individuen gecombineerd kunnen worden in één model, met als doel de voorkeuren van deze personen te bepalen. De gegevensverzameling waarop de empirische analyse is gebaseerd is dezelfde als die welke in hoofdstuk twee is gebruikt. In het hoofdstuk 3 zijn echter in aanvulling op de gegevens over keuzes, ook preferentiegegevens van dezelfde individuen meegenomen. Aangezien de voorkeuren van de consumenten die geanalyseerd worden stabiel kunnen worden verondersteld is de verwachting dat de schattingen verkregen op basis van elk van de beide type gegevens met elkaar verenigbaar zouden moeten zijn. Aan de andere kant zijn er echter ook aanwijzingen in de literatuur dat contexteffecten (zoals het type antwoordtaak) verschillende voorkeuren bij een individu kunnen oproepen. Dergelijke taakeffecten zouden ook kunnen optreden bij het beantwoorden van preferentie vs. keuzetaken en mogelijke verschillen in schattingen kunnen opleveren tussen de twee typen gegevens.

Om te onderzoeken of dergelijke verschillen inderdaad bestaan is het nuttig om de gegevens in een gecombineerd model te analyseren. Met dit doel is een econometrisch model ontwikkeld dat het schatten en toetsen van verschillen tussen de twee typen gegevens (keuzes en preferenties) mogelijk maakt. De keuzegegevens worden gemodelleerd met een multinomiaal logit model, terwijl de preferentiegegevens met een geordend respons model (ordered probit) worden beschreven. Een flexibele monotone transformatie van de preferentiescores op de onderliggende consumentenvoorkeuren is in het preferentiemodel mogelijk omdat antwoordcategorie-grenzen worden geschat in plaats van vooraf vastgelegd. Ook heterogeniteit tussen individuen is opgenomen en wel door random coëfficiënten. Deze coëfficiënten bepalen tevens (een deel van) de relatie tussen het keuze- en preferentiemodel. Hoofdstuk 3 bespeekt de schatting en identificatie van het gecombineerde model en ook de mogelijk grotere efficiëntie van een gecombineerd model ten opzichte van afzonderlijke modellen voor de twee typen gegevens.

Uit de toepassing van het model op de enquêtegegevens blijkt dat de modelschatting gebaseerd op de preferentiegegevens significant verschilt van het model gebaseerd op de keuzegegevens. Dit resultaat wijst erop dat er inderdaad taakeffecten optreden. Tegelijkertijd vinden we echter ook een sterke correlatie tussen de random coëfficiënten bij de twee typen gegevens. Dit resultaat veroorzaakt dat het gecombineerde model met verschillende structurele parameters voor elk type gegevens en correlaties tussen de random coëfficiënten, de keuzes en preferenties beter kan verklaren en voorspellen dan de twee afzonderlijke modellen voor elk van de gegevenstypen.

Hoofdstuk 4 beschrijft vervolgens een model voor een beperkt rationeel individu dat, hoewel niet volledig rationeel, toch een zekere vorm van berekenende rationaliteit hanteert. In dit model houdt de consument rekening met de kosten en moeite die verbonden zijn aan het cognitieve proces. Op basis van een berekening van de verwachte cognitieve kosten en de uitkomsten van verschillende mogelijke keuzeprocessen kiest de consument een keuzestrategie. De nutsfunctie van consument omvat in dit model zowel de verwachte kosten van het maken van de keuze als de uitkomst van de keuze. Dit kosten-baten perspectief maakt het mogelijk om te verklaren waarom keuzeprocessen variëren tussen verschillende keuzesituaties.

We ontwikkelen een theoretisch model van optimale inspanning in consumentenkeuzes. Het model bouwt voort op eerdere consumentenkeuzemodellen waarin alleen de produktkeuze wordt gemodelleerd. Deze eerdere modellen worden uitgebreid met een fase waarin consumenten eerst beslissen hoeveel moeite ze in een keuzeprobleem willen steken. Deze moeite wordt in het model afgewogen tegen de verwachte opbrengst van de keuze. De optimale inspanning in een keuzesituatie hangt af van de de inspanningskosten van de individuele consument, het verwachte nut van de gemaakt keuze en de complexiteit van de keuzetaak.

Om de empirische validiteit van het model te onderzoeken is een tweede enquête gehouden onder een consumentenpanel in Nederland en uitgevoerd door CentER*data*. Consumenten beantwoorden conjuncte keuzetaken over restaurants. Als maat voor de keuzeinspanning is bij elke vraag de antwoordtijd gemeten. Daarnaast is een produktbetrokkenheidschaal afgenomen bij consumenten op basis waarvan individuele maten voor de inspanningskosten (belangstelling voor het produkt) en de gepercipieerde complexiteit zijn berekend. Daarnaast is per keuzetaak het geschatte nutsverschil tussen de produkten en het aantal benodigde elementaire cognitieve informatieverwerkingsstappen berekend.

De inspanning (antwoordtijd) is in een regressiemodel uitgezet tegen de individuele betrokkenheidscore, de produktnutsverschillen en de elementaire cognitieve stappen. De resultaten zijn consistent met het theoretisch model en bevestigen de gedachte dat consumenten hun keuzestrategie aanpassen aan de verwachte kosten en opbrengsten van hun keuzeproces. De antwoordtijd was bijvoorbeeld hoger voor meer geïnteresseerde consumenten (met lagere inspanningskosten) en in keuzesituaties met grotere verschillen in nut tussen alternatieven of met een grotere complexiteit.

In hoofdstuk 5 tenslotte introduceren en toetsen we een nieuw model voor beperkt rationele keuzeprocessen. Het model staat toe dat consumenten hun keuzeproces vereenvoudigen door niet alle attributen in hun keuze te betrekken. Deze modelvorm sluit aan bij eerdere bevindingen in de literatuur die laten zien dat consumenten veelal geen volledige vergelijking maken tussen alle attributen van produkten. De belangrijkste aanname in dit model is dat dergelijke vereenvoudigingen gebaseerd zijn op een keuze van een aantal attributen dat wordt vergeleken. Dergelijke keuzeprocessen zijn waarschijnlijk het meest relevant voor situaties waarin gekozen moet worden tussen een relatief klein aantal alternatieven met relatief veel attributen.

Het model is gebaseerd op het mixed logit model waarin het produktnut in de keuze gebaseerd is op een beperkt aantal attributen. Heterogeniteit tussen individuen is opgenomen in de vorm van preferentieverdelingen voor elk attribuut. Een interne drempelwaarde voor een minimaal nutsverschil tussen attribuutniveaus bepaalt of een attribuut wel of niet in de keuze wordt meegenomen. Als het nutsverschil tussen attribuutniveaus te klein is wordt het niet in de keuze betrokken. Deze drempelwaardes zijn als random coëfficiënten gemodelleerd om verdere heterogeniteit in keuzeprocessen mogelijk te maken. Verschillende consumenten kunnen meer of minder uitgebreide keuzeprocessen doorlopen. Door random coëfficiënten voor de preferenties te schatten zijn ook variaties mogelijk in welke attributen een consument vergelijkt.

Het model wordt toegepast op de dezelfde gegevens als gebruikt in hoofdstuk 4. Er wordt echter ook gebruik gemaakt van aanvullende gegevens. Deze gegevens beschrijven welke attributen een consument zegt wel en welke niet te hebben gebruikt. Daarnaast is voor elke attribuut een belangrijkheidscore beschikbaar. Door deze aanvullende informatie toe te voegen kunnen de verschillende individuele keuzeprocessen worden ontrafeld en is het model geïdentificeerd. De modelschattingen worden verricht met behulp van Smooth Maximum Simulated Likelihood.

Onze resultaten laten zien dat respondenten met een hogere antwoordtijd lagere drempelwaardes hebben en dus meer attributen vergelijken. We vinden ook dat naarmate de complexiteit van de keuzetaak toeneemt, respondenten meer attributen beschouwen. Het structurele verband tussen preferenties en of een bepaald attribuut wel of niet wordt meegenomen in de keuze wordt geïllustreerd door de verdelingen te berekenen van de random coefficiënten gegeven de informatie over attribuut gebruik. Deze benadering is vergelijkbaar met de recent ontwikkelde aanpak van Revelt en Train (1999) om individuele preferentieparameters te bepalen gegeven een bepaald keuzepatroon bij de consument.

Samenvattend kan worden gesteld dat dit proefschrift empirisch bewijs levert voor beperkt rationeel gedrag bij consumenten en modellen introduceert die dergelijk gedrag kunnen beschrijven en verklaren. Het onderzoek laat zien dat dergelijke modellen gebaseerd op beperkt rationeel gedrag realistisch, en bovendien optimaal kunnen zijn als consumenten rekening houden met cognitieve kosten. In de verschillende hoofdstukken worden verschillende mogelijke modellen voorgesteld als alternatief voor het traditionele rationele nutsmaximaliserende keuzemodel.

Center for Economic Research, Tilburg University, The Netherlands
Dissertation Series

No.	Author	Title	Published
1	P.J.J. Herings	Static and Dynamic Aspects of General Disequilibrium Theory; ISBN 90 5668 001 3	June 1995
2*	Erwin van der Krabben	Urban Dynamics: A Real Estate Perspective - An institutional analysis of the production of the built environment; ISBN 90 5170 390 2	August 1995
3	Arjan Lejour	Integrating or Desintegrating Welfare States? - a qualitative study to the consequences of economic integration on social insurance; ISBN 90 5668 003 X	September 1995
4	Bas J.M. Werker	Statistical Methods in Financial Econometrics; ISBN 90 5668 002 1	September 1995
5	Rudy Douven	Policy Coordination and Convergence in the EU; ISBN 90 5668 004 8	September 1995
6	Arie J.T.M. Weeren	Coordination in Hierarchical Control; ISBN 90 5668 006 4	September 1995
7	Herbert Hamers	Sequencing and Delivery Situations: a Game Theoretic Approach; ISBN 90 5668 005 6	September 1995
8	Annemarie ter Veer	Strategic Decision Making in Politics; ISBN 90 5668 007 2	October 1995
9	Zaifu Yang	Simplicial Fixed Point Algorithms and Applications; ISBN 90 5668 008 0	January 1996
10	William Verkooijen	Neural Networks in Economic Modelling - An Empirical Study; ISBN 90 5668 010 2	February 1996
11	Henny Romijn	Acquisition of Technological Capability in Small Firms in Developing Countries; ISBN 90 5668 009 9	March 1996
12	W.B. van den Hout	The Power-Series Algorithm - A Numerical Approach to Markov Processes; ISBN 90 5668 011 0	March 1996
13	Paul W.J. de Bijl	Essays in Industrial Organization and Management Strategy; ISBN 90 5668 012 9	April 1996

No.	Author	Title	Published
14	Martijn van de Ven	Intergenerational Redistribution in Representative Democracies; ISBN 90 5668 013 7	May 1996
15	Eline van der Heijden	Altruism, Fairness and Public Pensions: An Investigation of Survey and Experimental Data; ISBN 90 5668 014 5	May 1996
16	H.M. Webers	Competition in Spatial Location Models; ISBN 90 5668 015 3	June 1996
17	Jan Bouckaert	Essays in Competition with Product Differentiation and Bargaining in Markets; ISBN 90 5668 016 1	June 1996
18	Zafar Iqbal	Three-Gap Analysis of Structural Adjustment in Pakistan; ISBN 90 5668 017 X	September 1996
19	Jimmy Miller	A Treatise on Labour: A Matching-Model Analysis of Labour-Market Programmes; ISBN 90 5668 018 8	September 1996
20	Edwin van Dam	Graphs with Few Eigenvalues - An interplay between combinatorics and algebra; ISBN 90 5668 019 6	October 1996
21	Henk Oosterhout	Takeover Barriers: the good, the bad, and the ugly; ISBN 90 5668 020 X	November 1996
22	Jan Lemmen	Financial Integration in the European Union: Measurement and Determination; ISBN 90 5668 021 8	December 1996
23	Chris van Raalte	Market Formation and Market Selection; ISBN 90 5668 022 6	December 1996
24	Bas van Aarle	Essays on Monetary and Fiscal Policy Interaction: Applications to EMU and Eastern Europe; ISBN 90 5668 023 4	December 1996
25	Francis Y. Kumah	Common Stochastic Trends and Policy Shocks in the Open Economy: Empirical Essays in International Finance and Monetary Policy; ISBN 90 5668 024 2	May 1997
26	Erik Canton	Economic Growth and Business Cycles; ISBN 90 5668 025 0	September 1997

No.	Author	Title	Published
27	Jeroen Hoppenbrouwers	Conceptual Modeling and the Lexicon; ISBN 90 5668 027 7	October 1997
28	Paul Smit	Numerical Analysis of Eigenvalue Algorithms Based on Subspace Iterations; ISBN 90 5668 026 9	October 1997
29	Uri Gneezy	Essays in Behavioral Economics; ISBN 90 5668 028 5	October 1997
30	Erwin Charlier	Limited Dependent Variable Models for Panel Data; ISBN 90 5668 029 3	November 1997
31	Rob Euwals	Empirical Studies on Individual Labour Market Behaviour; ISBN 90 5668 030 7	December 1997
32	Anurag N. Banerjee	The Sensitivity of Estimates, Inferences, and Forecasts of Linear Models; ISBN 90 5668 031 5	December 1997
33	Frans A. de Roon	Essays on Testing for Spanning and on Modeling Futures Risk Premia; ISBN 90 5668 032 3	December 1997
34	Xiangzhu Han	Product Differentiation, Collusion and Standardization; ISBN 90 5668 033 1	January 1998
35	Marcel Das	On Income Expectations and Other Subjective Data: A Micro-Econometric Analysis; ISBN 90 5668 034 X	January 1998
36	Jeroen Suijs	Cooperative Decision Making in a Stochastic Environment; ISBN 90 5668 035 8	March 1998
37	Talitha Feenstra	Environmental Policy Instruments and International Rivalry: A Dynamic Analysis; ISBN 90 5668 036 6	May 1998
38	Jan Bouwens	The Use of Management Accounting Systems in Functionally Differentiated Organizations; ISBN 90 5668 037 4	June 1998
39	Stefan Hochguertel	Householdsí Portfolio Choices; ISBN 90 5668 038 2	June 1998
40	Henk van Houtum	The Development of Cross-Border Economic Relations; ISBN 90 5668 039 0	July 1998
41	Jorg Jansen	Service and Inventory Models subject to a Delay-Limit; ISBN 90 5668 040 4	September 1998

No.	Author	Title	Published
42	F.B.S.L.P. Janssen	Inventory Management Systems: control and information issues; ISBN 90 5668 041 2	September 1998
43	Henri L.F. de Groot	Economic Growth, Sectoral Structure and Unemployment; ISBN 90 5668 042 0	October 1998
44	Jenke R. ter Horst	Longitudinal Analysis of Mutual Fund Performance; ISBN 90 5668 043 9	November 1998
45	Marco Hoeberichts	The Design of Monetary Institutions; ISBN 90 5668 044 7	December 1998
46	Adriaan Kalwij	Household Consumption, Female Employment and Fertility Decisions: A microeconometric analysis; ISBN 90 5668 045 5	February 1999
47	Ursula Glunk	Realizing High Performance on Multiple Stakeholder Domains: A Resource-based Analysis of Professional Service Firms in the Netherlands and Germany; ISBN 90 5668 046 3	April 1999
48	Freek Vermeulen	Shifting Ground: Studies on the Intersection of Organizational Expansion, Internationalization, and Learning; ISBN 90 5668 047 1	February 1999
49	Haoran Pan	Competitive Pressures on Income Distribution in China; ISBN 90 5668 048 X	March 1999
50	Laurence van Lent	Incomplete Contracting Theory in Empirical Accounting Research; ISBN 90 5668 049 8	April 1999
51	Rob Aalbers	On the Implications of Thresholds for Economic Science and Environmental Policy; ISBN 90 5668 050 1	May 1999
52	Abe de Jong	An Empirical Analysis of Capital Structure Decisions in Dutch Firms; ISBN 90 5668 051 X	June 1999
53	Trea Aldershof	Female Labor Supply and Housing Decisions; ISBN 90 5668 052 8	June 1999
54	Jan Fidrmuc	The Political Economy of Reforms in Central and Eastern Europe; ISBN 90 5668 053 6	June 1999
55	Michael Kosfeld	Individual Decision-Making and Social Interaction; ISBN 90 5668 054 4	June 1999

No.	Author	Title	Published
56	Aldo de Moor	Empowering Communities - A method for the legitimate user-driven specification of network information systems; ISBN 90 5668 055 2	October 1999
57	Yohane A. Khamfula	Essays on Exchange Rate Policy in Developing Countries; ISBN 90 5668 056 0	September 1999
58	Maurice Koster	Cost Sharing in Production Situations and Network Exploitation; ISBN 90 5668 057 9	December 1999
59	Miguel RosellÛn Cifuentes	Essays on Financial Policy, Liquidation Values and Product Markets; ISBN 90 5668 058 7	December 1999
60	Sharon Schalk	Equilibrium Theory: A salient approach; ISBN 90 5668 059 5	December 1999
61	Mark Voorneveld	Potential Games and Interactive Decisions with Multiple Criteria; ISBN 90 5668 060 9	December 1999
62	Edward Droste	Adaptive Behavior in Economic and Social Environments; ISBN 90 5668 061 7	December 1999
63	Jos Jansen	Essays on Incentives in Regulation and Innovation; ISBN 90 5668 062 5	January 2000
64	Franc J.G.M. Klaassen	Exchange Rates and their Effects on International Trade; ISBN 90 5668 063 3	January 2000
65	Radislav Semenov	Cross-country Differences in Economic Governance: Culture as a major explanatory factor; ISBN 90 5668 065 X	February 2000
66	Alexandre Possajennikov	Learning and Evolution in Games and Oligopoly Models; ISBN 90 5668 064 1	March 2000
67	Eric Gaury	Designing Pull Production Control Systems: Customization and Robustness; ISBN 90 5668 066 8	March 2000
68	Marco Slikker	Decision Making and Cooperation Restrictions; ISBN 90 5668 067 6	April 2000
69	Ruud Brekelmans	Stochastic Models in Risk Theory and Management Accounting; ISBN 90 5668 068 4	June 2000
70	Flip Klijn	A Game Theoretic Approach to Assignment Problems; ISBN 90 5668 069 2	June 2000

No.	Author	Title	Published
71	Maria Montero	Endogenous Coalition Formation and Bargaining; ISBN 90 5668 070 6	June 2000
72	Bas Donkers	Subjective Information in Economic Decision Making; ISBN 90 5668 071 4	June 2000
73	Richard Nahuis	Knowledge and Economic Growth; ISBN 90 5668 072 2	October 2000
74	Kuno Huisman	Technology Investment: A Game Theoretic Real Options Approach; ISBN 90 5668 073 0	October 2000
75	Gijsbert van Lomwel	Essays on Labour Economics; ISBN 90 5668 074 9	November 2000
76	Tina Girndt	Cultural Diversity and Work-Group Performance: Detecting the Rules; ISBN 90 5668 075 7	December 2000
77	Teye A. Marra	The Influence of Proprietary Disclosure Costs on the Decision to Go Public: Theory and Evidence; ISBN 90 5668 076 5	January 2001
78	Xiaodong Gong	Empirical Studies on the Labour Market and on Consumer Demand; ISBN 90 5668 078 1	February 2001
79	Kanat Camlibel	Complementarity Methods in the Analysis of Piecewise Linear Dynamical Systems; ISBN 90 5668 079 X	May 2001
80	Joost Driessen	Empirical Studies on the Pricing of Bonds and Interest Rate Derivatives; ISBN 90 5668 080 3	June 2001
81	Bram van den Broek	Uncertainty in Differential Games; ISBN 90 5668 081 1	June 2001
82	Ricardo Recht	Organisational Culture and Privatisation: A Case Study of the Argentinean Railway Sector; ISBN 90 5668 082 X	June 2001
83	Willem Verhagen	Inflation Targeting and Interest Rate Policy; ISBN 90 5668 083 8	June 2001
84	Vincent Verouden	Essays in Antitrust Economics; ISBN: 90 5668 086 2	June 2001
85	Rosalia Vazquez Alvarez	A Nonparametric Approach to the Sample Selection Problem in Survey Data; ISBN 90 5668 087 0	June 2001

No.	Author	Title	Published
86	Theo Leers	Public Pensions and Population Ageing: An Economic Analysis of Fertility, Migration, and Social-Security Policy; ISBN 90 5668 084 6	June 2001
87	Bernard Conlon	Consumer Rationality in Choice; ISBN 90 5668 085 4	June 2001

* Copies can be ordered from Thela Thesis, Prinseneiland 305, 1013 LP Amsterdam, The Netherlands, phone: + 31 20 6255429; fax: +31 20 6203395; e-mail: office@thelathesis.nl

BERNARD CONLON completed a Bachelor degree in Economics with Honours (specialising in Econometrics) in 1994 at The University of Sydney, Australia. Following, this he completed a Masters Degree with Honours in Economics/ Econometrics at the same institution, graduating in 1996. From 1996 to 2001 he conducted his PhD research at the CentER for Economic Research, Tilburg University, the Netherlands.

The dissertation concentrates on consumer choice and the ability of current modelling approaches to capture the underlying behaviour of the individual decision-makers. The standard assumption of a rational utility maximising individual and its implications for observed behaviour are examined and demonstrated empirically to be incompatible with actual consumer choices. In particular the complexity of the choice situation, and its various components, are found to be major determinants of the choice outcomes. Both the accuracy of the choice outcome and as well as the process leading to the decision are found to vary with the difficulty of the choice set. Framing effects are also seen to lead individuals to indicate different preferences depending on the setting of the decision task. Models that allow for these deviations from the behaviour predicted under standard modelling assumptions are developed and the implementation of such models is discussed and illustrated utilising two major consumer surveys for the Dutch population.

ISBN: 90 5668 085 4